Journal of Globe Scientific Reports (2024)

Journal of Globe Scientific Reports

journal homepage: www.journal-gsr.online

Paper Type: Original Article

The Research Progress and Challenges of Image Segmentation Technology in Marine Aquaculture

Jin Zhao[1], Shuo Lian[1], Taizhi Li[1]

1.College of computer science and engineering, Chongqing Three Gorges University

Abstract

As marine resources become increasingly scarce, marine aquaculture, an integral part of the marine economy, necessitates scientific management and rational utilization. Image segmentation technology for marine aquaculture, a critical tool for monitoring and managing aquaculture areas, has garnered widespread attention in research and application. This paper reviews the research progress in marine aquaculture image segmentation techniques, analyzes the advantages and limitations of various methods, and explores future development directions.

Keywords: Marine aquaculture; Image segmentation; Remote sensing monitoring; Deep learning; Smart agriculture

1. Introduction

Marine aquaculture, as a crucial component of the marine economy, plays an increasingly significant role in global food supply and the utilization of marine resources [1]. With the expansion of aquaculture activities, traditional monitoring and management methods have become insufficient to meet the demands of modern marine agriculture. The industry now urgently requires more efficient and precise technologies to optimize resource allocation, improve production efficiency, protect the marine ecological environment, and achieve sustainable development. Against this backdrop, marine aquaculture image segmentation technology has emerged as an important tool for monitoring and managing marine resources. Marine aquaculture not only enriches the human food supply and enhances the efficiency of marine resource utilization but also significantly contributes to the marine economy, technological advancements, and ecological environment protection. As global population growth and the demand for seafood increase, the marine aquaculture industry demonstrates vast potential [2]. Remote sensing technology, especially satellite remote sensing, has become a key means of monitoring marine aquaculture due to its extensive coverage and high temporal efficiency. Through remote sensing imagery, it is possible to monitor the distribution, scale, and changes in marine aquaculture areas in real-time, providing a basis for scientific management and decision-making [3]. In recent years, with the advancement of computer vision and deep learning technologies, marine aquaculture image segmentation has made significant progress, transitioning from traditional image processing methods to advanced algorithms based on deep learning, with substantial improvements in accuracy and efficiency. In the future, the development of this technology will focus more on enhancing model generalization, real-time processing capabilities, and multi-source data fusion.

2. Overview of Marine Aquaculture Image Segmentation Technology

Marine aquaculture image segmentation technology applies computer vision and image processing techniques to identify and differentiate marine aquaculture areas from remote sensing images [4]. With the development of computer vision, image segmentation methods have evolved from traditional algorithms to machine learning and, eventually, to deep learning. This technology is critical for effectively managing and monitoring marine aquaculture areas, as it helps researchers and managers obtain essential information such as spatial distribution, scale changes, and biological growth conditions in aquaculture regions. This chapter will delve into the application, advantages, disadvantages, and latest technological advances of these methods in marine aquaculture image segmentation.

2.1 Definition of Image Segmentation

Image segmentation is a fundamental technique in the field of computer vision. Its objective is to partition an image into several regions or objects with distinct semantics, ensuring that the pixels within each region share similar characteristics, such as color, brightness, or texture. In marine aquaculture, image segmentation refers to the process of analyzing and processing images from the aquaculture environment using image processing techniques to isolate specific target areas or objects from a complex background. In this context, the goal is typically to identify and extract specific aquaculture objects, such as fish, shellfish, seaweed, net cages, or floating rafts, and to distinguish these objects from surrounding environmental elements like water bodies, plankton, and seabed background regions. Through image segmentation, it is possible to accurately locate and measure the quantity, distribution, morphological characteristics, and growth status of these aquaculture objects, providing precise data support for the management and decision-making of aquaculture farms.

2.2 Characteristics of Marine Aquaculture Images

Marine aquaculture images possess unique characteristics, stemming from the complexity of the marine environment and the limitations of the imaging conditions. Compared to terrestrial or aerial images, marine aquaculture images face more challenges during acquisition and processing, such as lighting variations, background complexity, and dynamic environments. These characteristics impose higher demands on the application of image segmentation technology, necessitating more sophisticated algorithm design and processing methods. Table 1 outlines the main characteristics of marine aquaculture images.

Table 1: Characteristics of Marine Aquaculture Images

Feature	Description
High Dynamic Range	Marine aquaculture areas are affected by different lighting conditions, resulting in significant changes in image brightness.
Complex Background	The image background contains various natural and man-made elements, such as waves, boats, and other marine organisms, increasing background complexity.
Variable Biological Behavior	Cultivated marine organisms exhibit different characteristics in images due to behavioral changes, adding to the processing difficulty.
Multi-scale Features	Marine aquaculture areas include facilities of various sizes, such as cages and rafts, which appear at different scales in the images.

2.3 Classification of Image Segmentation Techniques

Marine aquaculture image segmentation techniques are diverse, and with the advancement of computer vision and image processing technologies, these techniques have gradually evolved from traditional methods to more advanced algorithms. Each segmentation technique offers unique advantages and is suited to specific scenarios and requirements. By classifying different image segmentation techniques, one can gain a clearer understanding of their applicable scope and technical characteristics, aiding in the selection of the most suitable solution. Table 2 presents the classification of common image segmentation techniques.

Table 2: Image Segmentation Techniques Classification

Classification	Description
Traditional Methods	Based on pixel features such as thresholding, edge detection, and clustering, these methods rely on low-level features like grayscale and color.
Machine Learning-based Methods	Utilize machine learning algorithms like Support Vector Machines (SVM) and Random Forests to segment images by learning features from labeled data, often requiring manual feature design and selection.
Deep Learning-based Methods	Represented by Convolutional Neural Networks (CNN), Fully Convolutional Networks (FCN), U-Net, Mask R-CNN, and DeepLab, these methods automatically learn multi-level features for segmentation with high accuracy and robustness.
Multi-modal Image Segmentation Methods	Integrate multi-source data (e.g., optical images and SAR data) for segmentation, leveraging the strengths of different sensors to improve accuracy and stability.

2.4 Traditional Image Segmentation Methods

Traditional image segmentation methods primarily include threshold segmentation, edge detection, region growing, and clustering techniques. These methods are effective in handling simple image segmentation tasks with low computational complexity, but they often face challenges in the complex environment of marine aquaculture.

(1) Threshold Segmentation

This is one of the most basic image segmentation methods, where one or more grayscale thresholds are set to segment the image into different regions. The advantage of this method lies in its simplicity and fast computation, making it suitable for scenarios where there is a significant contrast in grayscale values between the target and background. However, in the complex environment of marine aquaculture, factors such as uneven lighting and noise interference can lead to poor threshold segmentation performance, making it difficult to accurately distinguish target objects.

(2) Edge Detection

Edge detection is based on the rate of change in the grayscale values of an image (e.g., gradient) and determines object boundaries by detecting regions with significant changes in grayscale values. Classic edge detection algorithms include Canny, Sobel, and Laplace operators. Although edge detection is precise in extracting object edges, it may encounter issues such as discontinuous boundaries and significant edge detection errors when dealing with complex marine aquaculture images. For instance, waves or bubbles in the water may interfere with the accuracy of edge detection, leading to boundaries that do not accurately describe the target objects.

(3) Clustering Methods

Clustering methods such as K-means clustering and fuzzy C-means clustering treat image pixels as feature vectors and divide them into several categories through clustering algorithms [5]. These methods can segment different types of objects to some extent, but in marine aquaculture images, the diversity of target objects and the complexity of the environment often limit the effectiveness of clustering methods.

2.5 Machine Learning-Based Image Segmentation Methods

With the development of machine learning techniques, methods such as Support Vector Machines (SVM) and Random Forests have been introduced into the field of image segmentation. These methods build segmentation models by learning features from large amounts of labeled data and apply them to new image segmentation tasks. Compared to traditional image segmentation methods, machine learning-based segmentation techniques offer higher adaptability and precision, especially in handling complex backgrounds and multi-class targets.

(1) Support Vector Machine

SVM is a model commonly used for binary classification problems, which segments different classes of pixels by finding a hyperplane that maximizes the margin between classes. SVM performs well when handling high-dimensional data and small sample datasets, with strong theoretical support and good generalization capability. In marine aquaculture image segmentation, SVM can effectively distinguish target objects from the background under specific conditions, particularly when there is a clear distinction between the features of aquaculture objects and the background [6]. However, due to the complex backgrounds, lighting variations, and diverse object categories in marine aquaculture images, a single SVM model may struggle to handle these complex segmentation tasks. Additionally, the classification performance of SVM is highly dependent on feature selection and parameter tuning. Manually designed feature extraction methods may not fully capture the key information in marine aquaculture images, limiting the effectiveness of SVM. For multi-class segmentation tasks, SVM requires multiple binary classification combinations, increasing the complexity of the model.

(2) Random Forest

Random Forest is an ensemble learning algorithm that improves segmentation accuracy by constructing multiple decision trees and voting. It can handle multi-class segmentation tasks and has strong robustness and generalization ability. In marine aquaculture image segmentation, Random Forest can achieve relatively accurate segmentation by combining manually designed features, especially when dealing with highly diverse images, where it shows good stability. Despite its advantages in segmentation accuracy and robustness, the effectiveness of Random Forest still depends on the quality of feature extraction. If the input features do not adequately represent the key information in marine aquaculture images, segmentation performance may be affected. Moreover, Random Forest may face high computational costs when processing high-resolution marine aquaculture images, particularly in scenarios requiring real-time performance. Thus, although Random Forest can address the complexity of marine aquaculture images to some extent, its performance relies on accurate feature selection and optimized computational resources.

2.6 Deep Learning Techniques

In recent years, with the rapid development of deep learning technologies, convolutional neural network (CNN)-based image segmentation methods have gradually become mainstream in the field of image processing. These methods can automatically learn and extract multi-level features from large amounts of data by constructing deep neural network models, achieving more accurate and robust image segmentation. In marine aquaculture image segmentation, deep learning methods have shown great potential, effectively addressing the challenges of complex backgrounds, diverse target objects, and dynamic environments.

(1) FCN (Fully Convolutional Network)

FCN is one of the earliest deep learning networks applied to image segmentation [7]. By modifying traditional convolutional neural networks, FCN replaces fully connected layers with convolutional layers, allowing the input image to be directly mapped to the segmentation result. FCN can handle input images of any size and extracts multi-level image features through multiple convolutional layers. In marine aquaculture image segmentation, FCN can effectively identify and segment underwater aquaculture objects such as fish, net cages, and seaweed, with high segmentation accuracy and adaptability. Despite FCN's significant achievements in image segmentation, its segmentation results still have room for improvement in terms of detail. When dealing with high-resolution, complex-feature marine aquaculture images, FCN's segmentation boundaries may lack precision, especially in the edge regions of target objects, leading to blurred or inaccurate segmentation. Additionally, FCN's segmentation process relies on the gradual recovery of multi-layer convolutional features, which may result in the loss of some detailed information, affecting the final segmentation outcome.

(2) U-Net

U-Net is a deep learning model specifically designed for biomedical image segmentation, but due to its excellent segmentation performance, it has been widely applied to various image segmentation tasks [8]. U-Net uses a symmetric encoder-decoder structure, which efficiently captures multi-scale information in images and preserves detailed information during the segmentation process through skip connections. In marine aquaculture image segmentation, U-Net can handle complex backgrounds and multi-scale targets, producing results with rich details and precise boundaries, making it especially suitable for scenarios requiring high-precision segmentation, such as identifying and segmenting densely packed fish or fine seaweed. While U-Net excels in segmentation accuracy, its complex structure demands high computational resources, particularly when processing high-resolution marine aquaculture images, which may lead to longer training and inference times. Furthermore, U-Net's performance is highly dependent on the quality and quantity of training data. In data-scarce scenarios, the model may not fully learn the target features, resulting in suboptimal segmentation performance.

(3) Mask R-CNN

Mask R-CNN is another advanced deep learning image segmentation method that combines the advantages of object detection and semantic segmentation, enabling simultaneous object recognition and precise segmentation [9]. Mask R-CNN adds a segmentation branch to the original Faster R-CNN framework, allowing it to not only detect targets in marine aquaculture images but also generate high-precision segmentation masks. For complex marine aquaculture scenarios, such as images containing multiple types of aquaculture objects, Mask R-CNN can accurately segment various targets and distinguish between them, offering high application value. However, Mask R-CNN's computational complexity is high, requiring substantial resources for model training and inference, particularly when processing large-scale image data in marine aquaculture, which may result in high computational costs. Additionally, the training process of Mask R-CNN requires a large amount of precisely labeled sample data, and the cost of data acquisition and labeling is high. In data-scarce application scenarios, its segmentation performance may not meet expectations.

(4) Comprehensive Advantages and Challenges of Deep Learning Methods

Deep learning-based image segmentation methods perform exceptionally well in processing marine aquaculture images, effectively addressing challenges posed by complex backgrounds, diverse targets, and dynamic environments. Their main advantages include automatic feature extraction, multi-scale information capture, and high-precision segmentation. However, these methods typically rely on large amounts of labeled data and high-performance computing resources, leading to high costs for model training and inference. For applications with limited data or computing resources, further optimization of model structures or the adoption of strategies such as transfer learning is needed to enhance segmentation effectiveness and efficiency.

2.7 Multimodal Image Segmentation

Multimodal image segmentation refers to the integration of data from different sensors or imaging modes in segmentation tasks, leveraging multiple information sources to improve segmentation accuracy and robustness. In complex application scenarios such as marine aquaculture image segmentation, multimodal technology is of significant importance as it can integrate data from different modalities to fully capture the multidimensional features of target objects, thereby better addressing the limitations of single-modal image segmentation methods.

(1) Sources of Multimodal Data

In marine aquaculture, common sources of multimodal data include optical images, synthetic aperture radar (SAR) images, multispectral images, and hyperspectral images. Each of these different modalities offers unique features, such as optical images providing rich color and texture information, SAR images penetrating clouds and water surfaces to obtain clear images under adverse weather conditions, and multispectral and hyperspectral images capturing spectral characteristics of objects.

(2) Advantages of Multimodal Image Segmentation

The main advantage of multimodal image segmentation lies in its ability to utilize the combined features of different modalities, thereby improving segmentation accuracy and robustness. For example, in the marine aquaculture environment, a single optical image may be affected by lighting variations, reflections, and the complexity of the underwater environment, while SAR images can provide stable observation data under adverse weather conditions. By combining these two modalities, the limitations of single-modal segmentation can be effectively overcome, resulting in more reliable segmentation outcomes. Additionally, multimodal image segmentation can capture more comprehensive target information in the feature space of different modalities. For instance, optical images may not clearly distinguish certain aquaculture facilities from the background water color, but by integrating SAR and multispectral images, multimodal information fusion can better identify and segment these targets [10].

(3) Challenges of Multimodal Image Segmentation

Despite the clear advantages of multimodal image segmentation, its application also faces several challenges. First, the data structures, resolutions, and noise characteristics of different modalities may differ significantly, making effective data registration and feature fusion a key challenge. Second, the acquisition and processing of multimodal data usually require higher computational resources and complex algorithm designs, imposing greater demands on system real-time performance and efficiency. In the practical application of marine aquaculture image segmentation, the annotation cost of multimodal images is also higher, as annotating different modality images often requires the knowledge of domain experts. Moreover, how to effectively fuse information from different modalities while maintaining segmentation accuracy and reducing computational complexity remains an urgent issue to be addressed in multimodal image segmentation methods.

(4) Multimodal Deep Learning Models

With advancements in deep learning, more research has begun exploring how to integrate multimodal data into deep learning frameworks to achieve more accurate image segmentation. Typical multimodal deep learning models include multi-branch networks, where each branch processes data from different modalities, and features are fused in subsequent network layers. This approach leverages the strong feature extraction capabilities of deep learning to fully exploit the information in each modality, thereby improving segmentation accuracy.

In marine aquaculture image segmentation, applying multimodal deep learning models can significantly enhance the understanding of complex scenes. For instance, using multimodal U-Net or multimodal Mask R-CNN can achieve detailed segmentation results while retaining the features of each modality. These models often combine optical images with SAR images or multispectral and hyperspectral images to capture more comprehensive environmental information, thereby better identifying and segmenting target objects within aquaculture areas.

3. Current Status and Challenges

3.1 Current Status

The application of image segmentation technology in marine aquaculture has made significant progress. While traditional segmentation methods, such as threshold segmentation, edge detection, and region growing, still have their use cases, their limitations are becoming increasingly apparent with the growing complexity of the environment. To tackle more complex segmentation tasks, machine learning-based methods, such as Support Vector Machines (SVM) and Random Forests, have been introduced, enhancing segmentation accuracy through feature learning from data. However, these methods rely on feature engineering and data annotation and may face performance bottlenecks when dealing with diverse targets.

In recent years, the field of marine aquaculture image segmentation has seen rapid technological advancements, particularly with deep learning-based methods becoming the mainstream. Currently, deep learning models like U-Net, Mask R-CNN, and DeepLab have demonstrated exceptional performance in marine aquaculture image segmentation. Fully Convolutional Networks (FCNs) and their variants, such as U-Net, with their powerful feature extraction and multi-scale processing capabilities, can accurately segment target objects within aquaculture areas, including fish, shellfish, and aquaculture facilities. In multimodal image segmentation, combining optical images with

Synthetic Aperture Radar (SAR) images, multispectral, and hyperspectral images has shown significant advantages. These multimodal methods effectively overcome issues such as lighting variations, noise interference, and resolution limitations present in single-modal images, resulting in more precise and robust segmentation outcomes.

3.2 Challenges

Despite the progress made in marine aquaculture image segmentation, several challenges remain. Marine aquaculture images are often affected by factors such as lighting variations, plankton, and bubbles, leading to unstable image quality. These issues introduce noise and occlusions in the images, making it difficult for segmentation algorithms to accurately identify target objects [11]. Additionally, the diversity of target objects in marine aquaculture, including various species of fish, shellfish, and seaweed, presents significant variations in shape, color, and texture. Traditional segmentation methods and single-feature machine learning algorithms may not fully capture these characteristics, thereby affecting segmentation results.

The dynamic nature of the marine environment, such as waves, tides, and the behavioral patterns of aquaculture organisms, causes frequent changes in the appearance and location of target objects. This dynamism increases the complexity of segmentation tasks, and existing models may exhibit instability when handling these changes. Furthermore, deep learning models typically require substantial computational resources and storage space. When processing high-resolution, large-scale datasets, the training and inference processes can be time-consuming, significantly increasing the demand for computational resources.

High-quality data annotation is fundamental to training deep learning models, but in the marine aquaculture environment, data annotation is costly, time-consuming, and the quality of annotations directly impacts model performance [12]. Automated data annotation methods are still in the exploratory stage and have not yet fully resolved issues related to annotation efficiency and accuracy. Although deep learning models perform well on training datasets, they may exhibit insufficient generalization capabilities when confronted with unseen samples or data from different environmental conditions. Improving the adaptability and robustness of these models remains a critical area of focus.

Facing these challenges, future research may focus on optimizing data preprocessing and augmentation techniques, enhancing the robustness of algorithms, developing efficient computational frameworks, and improving automated annotation technologies. These efforts will help advance marine aquaculture image segmentation technology, making it more efficient and reliable in practical applications.

4. Conclusion

Marine aquaculture, as a vital component of the global marine economy, plays a crucial role in ensuring food supply and promoting sustainable development. Image segmentation technology, particularly deep learning and multimodal image segmentation methods, has shown significant application potential in marine aquaculture monitoring. By accurately identifying and segmenting aquaculture objects in images, these technologies can effectively improve resource management and environmental protection efficiency. Although current technologies have made notable strides in accuracy and robustness, challenges remain in data complexity, annotation difficulty, computational resource requirements, feature fusion, and model generalization capabilities. Future research should focus on optimizing model structures, improving computational efficiency, refining data processing and annotation methods, and enhancing model adaptability. Through continuous technological innovation and practical application, marine aquaculture image segmentation technology is expected to play an increasingly critical role in safeguarding the marine ecological environment, enhancing aquaculture production efficiency, and supporting sustainable development goals.

Acknowledgement

The work described in this paper was supported in part by the Chongqing Graduate Student Research Innovation Program (CYS240759).

References

[1] Xu L, Hu Z, Zhang C, et al. Remote Sensing Image Segmentation of Mariculture Cage Using Ensemble Learning Strategy[J]. Applied Sciences, 2022, 12(16): 8234.

[2] Zhang H, Gui F. The application and research of new digital technology in marine aquaculture[J]. Journal of Marine Science and Engineering, 2023, 11(2): 401.

[3] Yu C, Hu Z, Li R, et al. Segmentation and density statistics of mariculture cages from remote sensing images using mask R-CNN[J]. Information Processing in Agriculture, 2022, 9(3): 417-430.

[4] Minaee S, Boykov Y, Porikli F, et al. Image segmentation using deep learning: A survey[J]. IEEE transactions on pattern analysis and machine intelligence, 2021, 44(7): 3523-3542.

[5] Dhanachandra N, Manglem K, Chanu Y J. Image segmentation using K-means clustering algorithm and subtractive clustering algorithm[J]. Procedia Computer Science, 2015, 54: 764-771.

[6] Rubbens P, Brodie S, Cordier T, et al. Machine learning in marine ecology: an overview of techniques and applications[J]. ICES Journal of Marine Science, 2023, 80(7): 1829-1853.

[7] Long J, Shelhamer E, Darrell T. Fully convolutional networks for semantic segmentation[C]//Proceedings of the IEEE conference on computer vision and pattern recognition. 2015: 3431-3440.

[8] Ronneberger O, Fischer P, Brox T. U-net: Convolutional networks for biomedical image segmentation[C]//Medical image computing and computer-assisted intervention–MICCAI 2015: 18th international conference, Munich, Germany, October 5-9, 2015, proceedings, part III 18. Springer International Publishing, 2015: 234-241.

[9] Ditria E M, Lopez-Marcano S, Sievers M, et al. Automating the analysis of fish abundance using object detection: optimizing animal ecology with deep learning[J]. Frontiers in Marine Science, 2020, 7: 429.

[10] Yu H, Wang F, Hou Y, et al. CMFPNet: A Cross-Modal Multidimensional Frequency Perception Network for Extracting Offshore Aquaculture Areas from MSI and SAR Images[J]. Remote Sensing, 2024, 16(15): 2825.

[11] Liu H, Ma X, Yu Y, et al. Application of deep learning-based object detection techniques in fish aquaculture: a review[J]. Journal of Marine Science and Engineering, 2023, 11(4): 867.

[12] Sun M, Yang X, Xie Y. Deep learning in aquaculture: A review[J]. J. Comput, 2020, 31(1): 294-319.