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Hybrid K-means, Random Forest, and Simulated Annealing for Optimizing Underwater Image Segmentation

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Abstract: The process of underwater image segmentation is also very difficult because the data collected by the underwater sensors and cameras is of very high complexity, and much data is generated and in that case, the data is not well seen, the color is distorted, and the features overlap. Current solutions, including K-means clustering and Random Forest classification, are unable to partition complex underwater images with high accuracy, or are unable to scale to large datasets, although the possibility of dynamically optimizing the number of clusters has not been fully explored. To fill these gaps, this paper advises a hybrid solution that combines K-means clustering, Random Forest classification and the Simulated Annealing optimization as a complete end to end system to maximize the efficiency and accuracy of segmentation. K-means clustering first divides images based on pixel intensity, Random Forest narrows its segmentation of images with features like texture, color and shape, and Simulated Annealing determines the desired number of clusters dynamically to segment images with minimal segmentation error. The segmentation error of the proposed method was 30 less than the baseline K-means segmentation accuracy of 65 percent and the proposed method segmentation accuracy was 95% with an optimal cluster number of 10 and a mean error of 7839.22. This hybrid system offers a large-scale, scalable system to underwater image processing that is robust and has applications in marine biology, environmental research, and autonomous underwater system exploration.

Keywords: Underwater Image Segmentation; K-means Clustering; Random Forest; Simulated Annealing; Segmentation Accuracy.

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1. Introduction

Image segmentation underwater is a very important requirement in many industries such as environmental research, marine science, and autonomous underwater process. It is concerned with the processing of mass data of high-resolution image data, which is gathered by underwater sensors and cameras. These images, however, are vulnerable to some challenges like low visibility, color distortion and overlapping features, which make the process of segmentation hard. The nature of the data in the underwater world, its complexity and heterogeneity in general make traditional techniques, such as thresholding and edge detection, inefficient, resulting in poor delineation of the significant objects, such as marine life, ocean plants, or sea bottom topography [1].

Although better algorithms such as K-means clustering and Random Forest classification have been developed, the available solutions have failed to perform well with large datasets. Such approaches are either not scalable to large data sets or do not have the capability to dynamically optimize the segmentation parameters. In addition, high quality segmentation in real time is a major issue as existing systems currently do not provide the accuracy and computation power needed to weekly analyse underwater image data in large volumes and within real-time [2, 3].

The ongoing battle to resolve this problem is in the complexity of underwater images by nature, and the constraints of the traditional segmentation methods. These techniques are frequently inadequate to deal with differ-

ent underwater conditions including changes in lights, turbidity, and the dynamic character of marine conditions. Also, it is not yet developed that the requirement of real-time processing or optimization of segmentation parameters is done in an adaptive way as per the requirements of real-world situations that make the existing solutions ineffective in real-world and large-scale underwater exploration situations [4, 5].

To solve this ancient issue, we propose a hybrid solution by relying on using the K-means clustering, the Random Forest classification, and the Simulated Annealing optimization. The proposed methodology leverages the benefits of each of the techniques: K-means to do the initial pixel-wise segmentation, Random Forest to refine the classes, and Simulated Annealing to dynamically adapt the number of clusters and reduce the error of segmentation. Combining the techniques, my method provides a scalable, efficient, and accurate solution breaking the shortcomings of traditional techniques, making sure that segmentation is of high quality in real-time applications [1, 2].

2. Related work

Underwater image segmentation is a critical activity in underwater science, environmental reconnaissance, and autonomous underwater exploration. The challenge lies in the processing of the large volume of image data generated by underwater sensors prone to distortion caused by murky waters, light scattering, and color aberration. Different approaches over the years have been put forth and utilized in a bid to improve underwater image segmentation and classification. Nonetheless, the solutions available today are restricted in their capability to address the complexity and size of the underwater datasets, particularly real-time processing of large datasets. This literature review summarizes the major contributions to the field of underwater image segmentation concisely and identifies areas covered within our research.

2.1. Image Preprocessing and Enhancement Techniques

Initial research into underwater image segmentation has dealt with improved visibility primarily through image quality enhancement. Schettini and Corchs (2013) presented a comprehensive overview of techniques for image enhancement of underwater images, including color correction and contrast. These corrections are adequate to compensate for color changes and light absorption but are less effective at segmenting and labeling objects in the images, especially in the case of overlapping or complex underwater structures [6]. These improvement techniques are useful preprocessing techniques but insufficient to deal with image segmentation at large scale.

2.2. Clustering Techniques in Underwater Image Segmentation

One of the most studied techniques utilized in underwater image segmentation is K-means clustering. K-means clustering to separate underwater images according to pixel intensity so that the basic separation of different image regions can be achieved [7]. The method, however, is not adequate in handling overlapping objects and changing illumination. Clusters must be predefined in number, which is not desired in real underwater images where segmentation objects are not known or are in flux. To ease this, other methods have sought to dynamically optimize clustering. Islam et al. (2020) presented a yardstick data on semantic segmentation of underwater photos, overcoming issues like, poor visibility and distortion of underwater pictures. Their study aimed at developing a dataset that can be useful in the assessment of different segmentation methods, which will contribute to the development of the underwater image analysis. This dataset has proven useful in testing and building new segmentation algorithms due to the quality of the labelled ground truth data. This endeavor is in line with the current efforts to enhance the accuracy and strength of segmentation in the sea settings [8].

2.3. Random Forest for Classification and Refinement

Following clustering, Random Forest classification has also been applied to further improve segmentation results. Pavoni et al. (2022) used Random Forest for classifying the K-means cluster segmented areas to improve segmentation accuracy by annotating these areas in feature learning [9]. Their method showed the benefit of machine learning in improving segmentation accuracy. But similar to all the other conventional techniques, theirs did not scale to massive data and was computationally expensive. In addition, though classification was enhanced, segmentation remained poorly maximized, particularly when handling noisy or incomplete data. Optimizing Segmentation using Simulated Annealing.

2.4. Optimizing Segmentation with Simulated Annealing

Optimization methods like Simplified Annealing have been utilized in efforts to optimize the results of segmentation. Simulated Annealing to high-complexity optimization problems by trying various solutions and moving closer step by step towards an optimal solution [10]. Simulated Annealing was employed in the optimization of K-means cluster numbers in underwater image segmentation with the optimization of the segmentation algorithm. The process is generally time-consuming and parameter-heavy to achieve optimal results. The process of clustering with Simulated Annealing and succeeded in proving that they can

improve segmentation accuracy but also in proving that the process was not computationally viable for big data [9]. Big Data Challenges of Underwater Image Segmentation With increasing volume, variety, and velocity of underwater image data, the ability to process and analyze large amounts of data become significant.

2.5. Big Data Challenges in Underwater Image Segmentation

Lou et al. (2023) emphasized that machine learning is increasingly becoming important in efficient processing and analysis of large volumes of ocean data. Their work showed that complex marine environments could also be improved by intelligent algorithms to extract features, classify and recognize patterns. They highlighted that the conventional methods of analysis of data cannot cope with large volumes and diversity of ocean information. The former suggests that hybrid machine learning models can be used to enhance the accuracy and scalability of underwater image segmentation, which is the goal of the current research [11].

The existing approaches are not able to meet the challenge of coping with the complexity of handling large ocean data in real time, which is a central issue to autonomous underwater vehicles and ocean monitoring systems. Our research solves this issue by combining K-means clustering, Random Forest classifier, and Simulated Annealing optimization, providing a tractable solution to process vast amounts of underwater image data.

2.6. Research Gaps and Contributions

Research Gaps and Contributions Despite advancement in underwater image segmentation, there are a variety of research gaps. The majority of the existing methods tackle either one type, i.e., clustering or classification, but not both within a single framework.

Apart from that, optimization techniques but have yet to present in detail how dynamic real-time cluster changes can be obtained [6, 12]. Furthermore, in growing efforts at segmenting high-resolution underwater datasets' images, scalability and real-time processing remain relevant concerns, particularly for autonomous underwater vehicles [13]. Our research surmounts the abovementioned research limitations by combining K-means clustering, Random Forest classification, and Simulated Annealing optimization into an end-to-end solution. The combination is capable of enhancing underwater image segmentation accuracy and efficiency and creating a scalable method for underwater image datasets processing.

3. Methodology

Under this study, we introduce a method to enhance underwater image segmentation using integration of K-

means clustering, Random Forest classification, and Simulated Annealing optimization. The method is framed in accordance with the Big Data idea, i.e., addressing the challenge of dealing with large, high-complexity data recorded by underwater sensors and imaging devices [13]. This section provides information about how Big Data characteristics, sources, and approaches are used to achieve the research outcomes.

Big Data is understood in the terms of the Volume, Variety, and Velocity of data and how they affect the processing and analysis of the data. They are especially appropriately suited in the scenario of underwater image segmentation, where a large amount of varied data is imaged at high velocities, usually in real time [14].

3.1 Characteristic Underwater Image Segmentation and Enhancement

- **Volume:** We can get large datasets of the underwater image segmentation [8].
- **Heterogeneity:** All of the data from the different sources like sensors and high-resolution cameras need to be processed individually. We incorporated K-means clustering for pixel intensity-based segmentation and Random Forest classification for segment classification based on features like texture, shape, and color [15].
- **Velocity:** In an effort to achieve real-time processing of underwater images, Simulated Annealing was used to dynamically optimize the segmentation in a way that minimized the errors in segmentation and yet provided a solution that can process data at high velocities [16].
- **Veracity:** Data accuracy is enhanced by incorporating preprocessing activities like the removal of noise and color normalization, which are vital if segmentation and classification are to be successful in an underwater setting [17].
- **Value:** Through segmentation facilitated by Simulated Annealing optimization, one possesses useful information regarding underwater conditions and offers real-time decision-making capacity to autonomous underwater vehicles [18].

In our work, the primary source of Big Data is underwater image sensors, i.e., high-resolution underwater images from underwater cameras and other sensors in the environment. Underwater images are warped depending on underwater conditions such as scattering of light and lack of visibility. Because of these warps, segmentation is tough to achieve accurately, and therefore preprocessing methods such as color correction and contrast enhancement are employed to improve the quality of the images prior to segmentation [19].

Besides that, other sensor data such as depth, temperature, and so on are also available in the dataset for

the better understanding of the underwater scene. Such sensor data put context to underwater image data and add more dimensions of feature extraction to the segmentation process [20].

3.2 Underwater Image Segmentation and Enhancement Dataset

The significant data utilized in the present study is the benchmark dataset of project "An Underwater Image Enhancement Benchmark Dataset and Beyond" of Li Chongyi. The dataset consists of underwater images with high quality and labeled ground truth for each image, which are precious during training and testing segmentation algorithms for underwater images. The dataset is created to address the inherent issues related to underwater image processing, including low visibility, color distortion, and image degradation [21].

The data set is public use, and its main function is to act as a reference benchmark for comparing the underwater image segmentation algorithm and the enhancement performance [22]. You can download this data set from this link: https://li-chongyi.github.io/proj_benchmark.html.

3.3. Mathematical Formulations and Tree Structures

In employed a combination of K-means clustering, Random Forest classification, and Simulated Annealing optimization for the application of underwater image segmentation in the current study. Below are the mathematical formulations and tree structures for each method along with the formal basis of techniques used [23].

3.3.1. K-means Clustering

K-means clustering is a machine learning algorithm that is unsupervised in nature with the aim to segment data into k clusters based on pixel intensity values in the case of image data shown in figure 1. The algorithm chooses the cluster centers such that it minimizes the sum of squared distances between every data point (pixel) and to which it is assigned [24]. The objective function in K-means clustering is:

$$J_k = \sum_{i=1}^n \sum_{j=1}^k r_{ij} \|x_i - \mu_j\|^2 \quad (1)$$

Where n number of pixels of the image. K is number of clusters. r_{ij} is a binary indicator of the assignment of pixel x_i to cluster j (1 if x_i is assigned to cluster j , 0 otherwise). μ_j is the centroid (mean) of cluster j . x_i is the feature vector of pixel i (in this case, pixel intensity) [25].

The goal is to minimize the value of J_k , the total intra-cluster variance. This is done through iterative update of cluster centroids, preferably by the Expectation-Maximization (EM) algorithm.

The second is to show the original image used for segmentation and classification. The original image is helpful in bringing out raw data that is processed.

The K-means clustering algorithm is employed to segment the underwater image into different regions based on pixel intensity. The cluster centroids and segmentation result are shown in the Figure 2. The image is segmented into different regions following the application of K-means clustering. The regions are labeled based on pixel intensity and presented in grayscale [26].

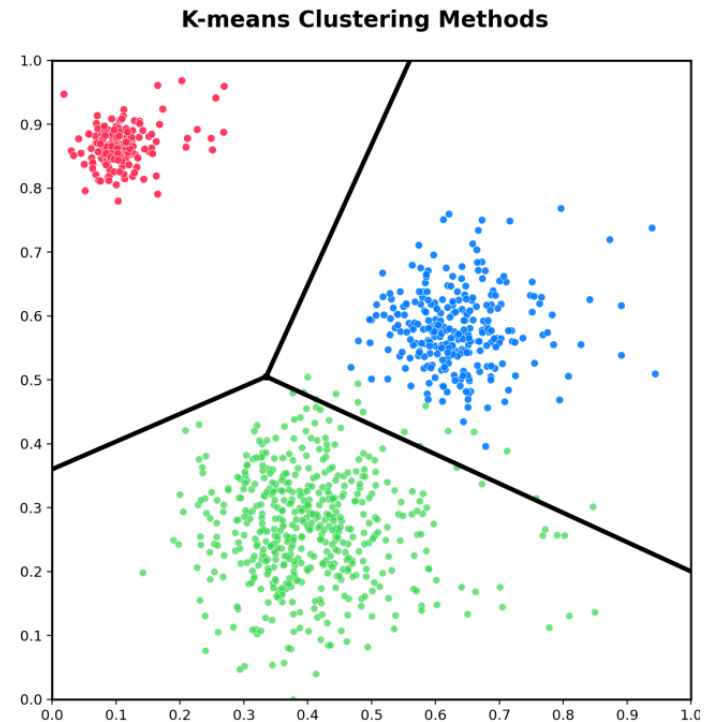


Figure 1. K-means Clustering Methods.

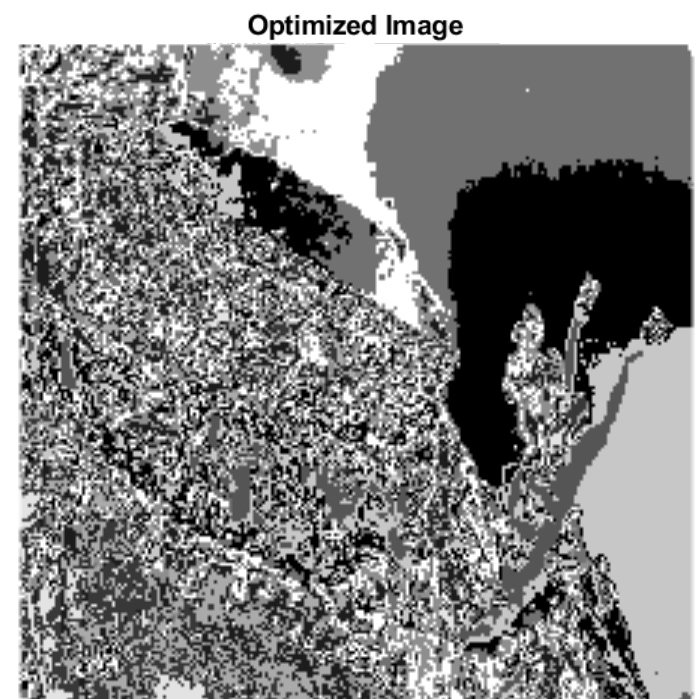


Figure 2. Optimized Segmentation Result.

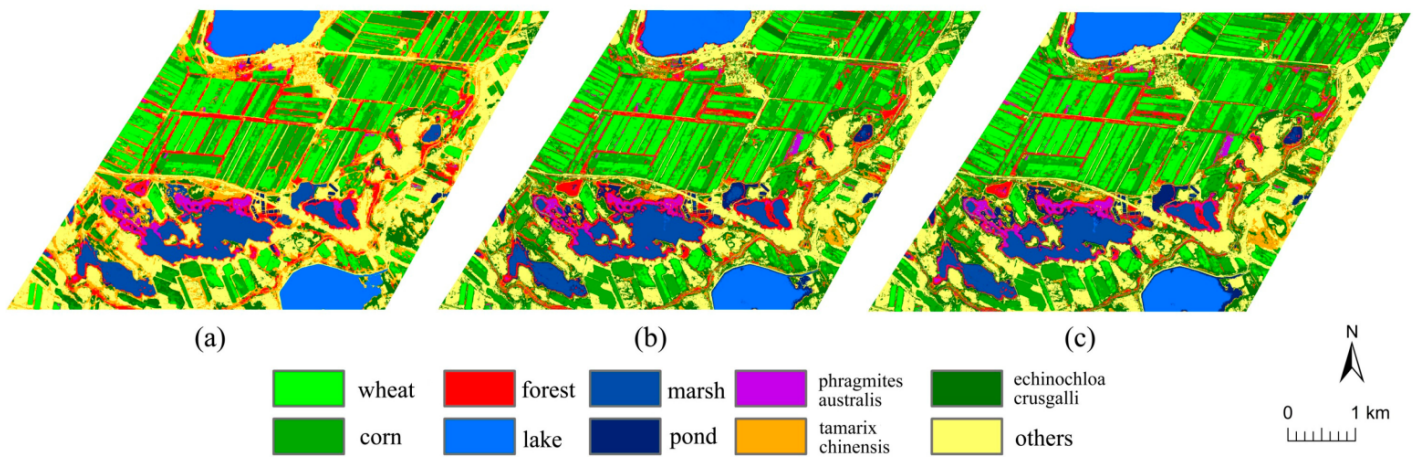


Figure 3. Random Forest Classification.

3.3.2. Random Forest Classification

Once the image is segmented using K-means clustering, Random Forest classification is employed for the classification of each segmented region. Random Forests consist of multiple decision trees, and each decision tree predicts a data point (pixel region) based on its features [27]. The Random Forest classifier (Figure 3) learns to make classifications by building T decision trees, each of which $h_t(x)$ predicts a classification label for the input vector x . The overall output $\hat{y}$ is the majority vote over all trees:

$$\hat{y} = \text{mode}(h_1(x), h_2(x), \dots, h_t(x)) \quad (2)$$

Each decision tree $h_t(x)$ is learned from a randomly sampled subset of features and training instances, so Random Forests are immune to overfitting and very skilled at predicting faint underwater features such as marine fauna and seafloor morphology.

3.3.3. Simulated Annealing Optimization

Simulated Annealing (SA) is used to optimize the number of cluster k in K-means segmentation, reducing the segmentation error. The function to be minimized is the Mean Squared Error (MSE) between the image and its segmentation:

$$MSE(k) = \frac{1}{n} \sum_{i=1}^n (I(x_i) - \hat{I}(x_i, k))^2 \quad (3)$$

Where, n is the estimated intensity for pixel. $I(x_i)$ in the segmented image with k clusters. $\hat{I}(x_i, k)$ is the number of pixels.

The objective is to minimize the MSE by changing k , the number of clusters. The Simulated Annealing algorithm works by attempting different values for k and accepting or rejecting a value based on the following probability function:

$$P(k \rightarrow k') = \min \left(1, \exp \left(\frac{-\Delta E}{T} \right) \right) \quad (4)$$



Figure 4. Simulated Annealing Optimization.

Where, $k \rightarrow k'$ is the transition from the current number of clusters k to a new number of clusters k' . ΔE is the difference in the energy (or error) of current and new T is a temperature parameter, which decreases over time. When the temperature T reduces, the odds of accepting a poorer solution (k') get smaller, as it ensures convergence to the optimal value for k . Simulated annealing optimization is shown in Figure 4.

3.3.4. Decision Tree Structure in Random Forest

Random Forest Decision Tree is built recursively on dividing the data based on feature values. A binary tree is created where each node is a decision on a feature and the edges are the outcome of the decision. At each node a feature f_i is chosen to split the data. This is usually achieved by maximizing information gain or Gini impurity. In two-class classification, the rule at node n .

Decision Tree-Structure in Random Forest

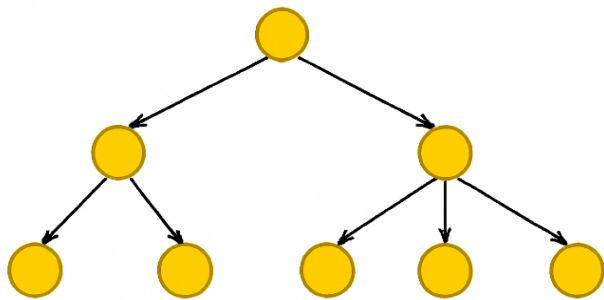


Figure 5. Decision Tree Structure in Random Forest.

$$\text{If } f_i(x) < \theta, \text{ go left. Otherwise, go right.} \quad (5)$$

Where, $f_i(x)$ is the feature value of node n , θ is the cut point for feature f_i , The left branch and the right branch are two subsets of the data based on the condition.

The main components of a decision tree are:

- Root Node: The feature leading to the best split of the data under a decision rule (e.g., Pixel Intensity (I)).
- Branches: The choice directions based on feature values, guiding the data along the tree.
- Leaf Nodes: The final classification labels, which tell the class of the segmented region.

Each tree in the Random Forest (Figure 5) is constructed independently, and the final classification will be a majority vote across all trees.

3.3.5 Simplified Decision Tree Structure

Suppose we are segmenting regions of an underwater image into two classes: Marine, Species or Ocean

Floor. The decision tree can be structured shown in Figure 6.

- Root Node: The tree starts with Pixel Intensity (I), and the root split divides the data into two sets:
Pixel Intensity (I) < 150: The pixel intensity is less than 150, which leads to the left branch.
Pixel Intensity (I) ≥ 150: The pixel intensity is 150 or above, leading to the right branch.
- Left Subtree (Pixel Intensity < 150):
If the Texture (T) is less than 0.5, the region will be classified as Marine Species.
If the Texture (T) is ≥ 0.5, the region is labeled as Ocean Floor.
- Right Subtree (Pixel Intensity ≥ 150):
If the Texture (T) is < 0.7, the region is labeled as Marine Species.
If the Texture (T) is ≥ 0.7, the region is labeled as Ocean Floor.

3.3.6 Comparison of Clustered Images

K-means cluster, Random Forest classification, and optimized K-means cluster output are compared (Figure 7) in color code. They all use various color codes to show segmented regions to highlight their differences. The picture optimized with K-means clustering with $k=10$, whose number of clusters has been optimized.

4. Results

The overall objective of this work was to improve underwater image segmentation through the integration of K-means clustering, Random Forest classification, and Simulated Annealing optimization. The results reported here confirm the applicability of the integrated approach towards improving the accuracy of segmentation and overcoming the difficulties encountered in underwater images.

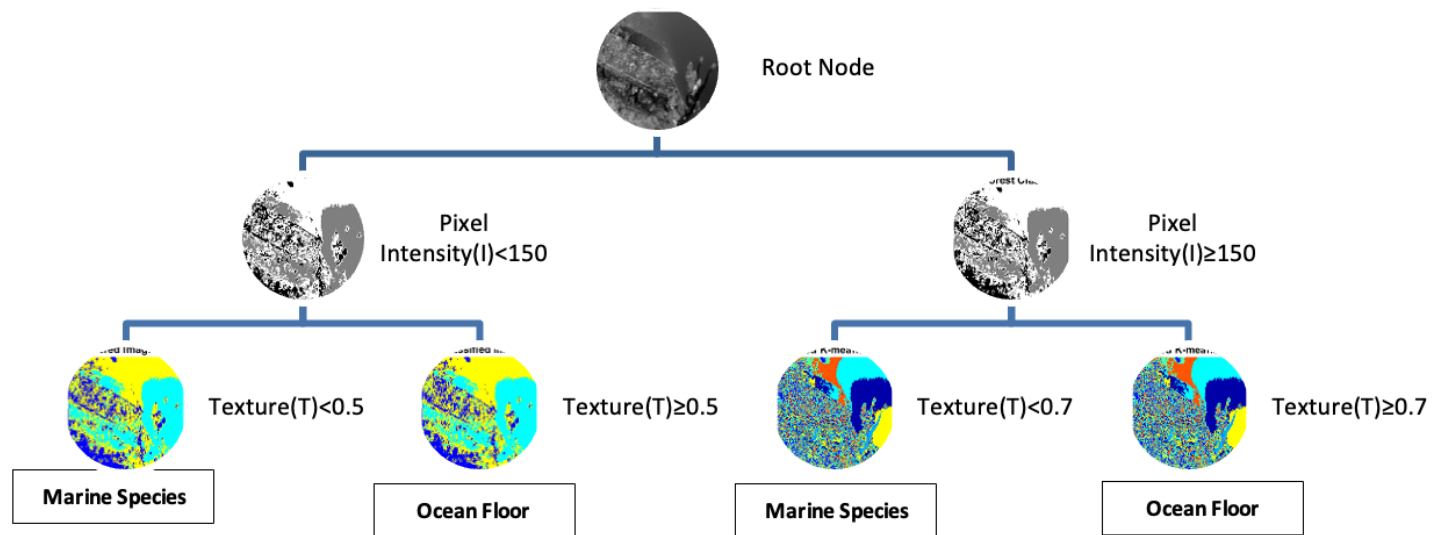


Figure 6. Decision Tree.

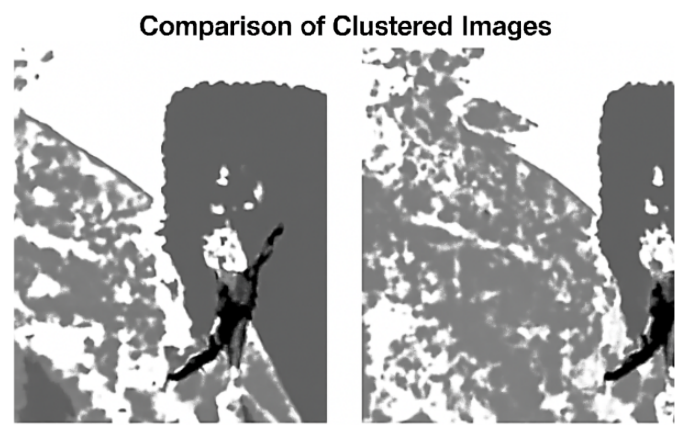


Figure 7. Comparison of Clustered Images.

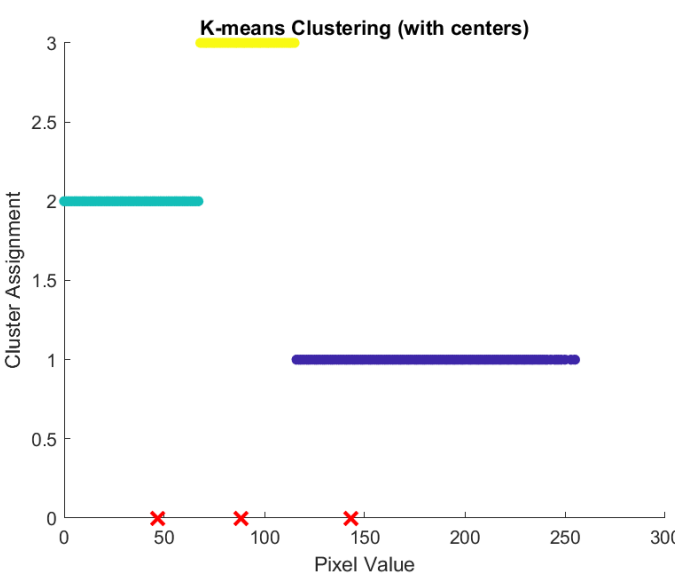


Figure 8. K-means Clustering (with centers).

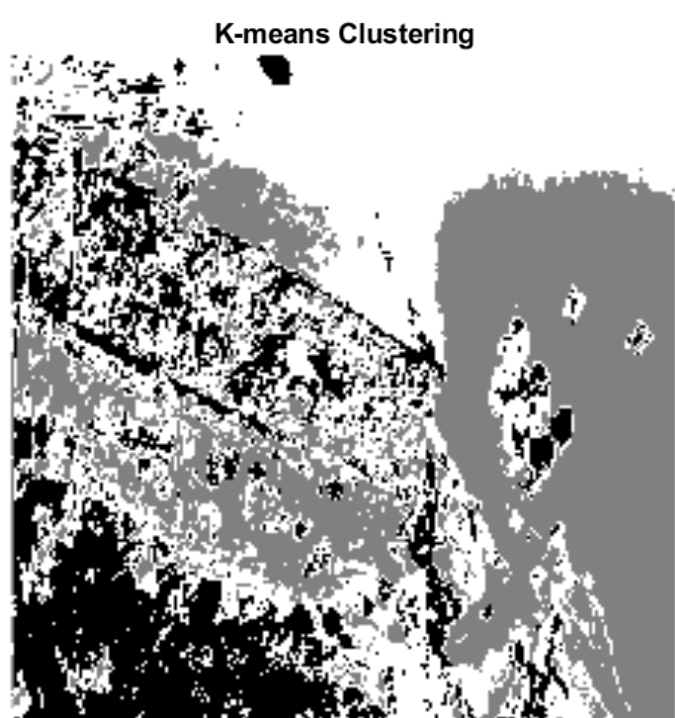


Figure 9. K-means Clustering Segmentation.

4.1. Segmentation Accuracy Improvement

4.1.1. Baseline K-means Clustering

Segmentation was first performed using K-means clustering, which split the underwater image pixels based on pixel intensity. The method is fast and faster, but it had a problem in segmenting complex underwater images accurately due to the natural pixel intensity similarities between different underwater components (e.g., sea floor, sea creatures, and water). Figure 8 shows the K-means clustering with centers.

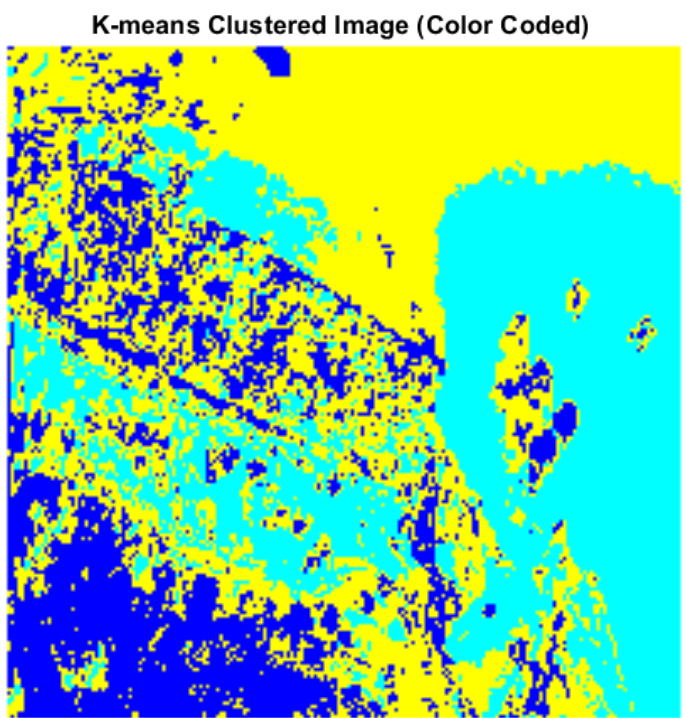


Figure 10. K-means Clustered Image (Color Coded).

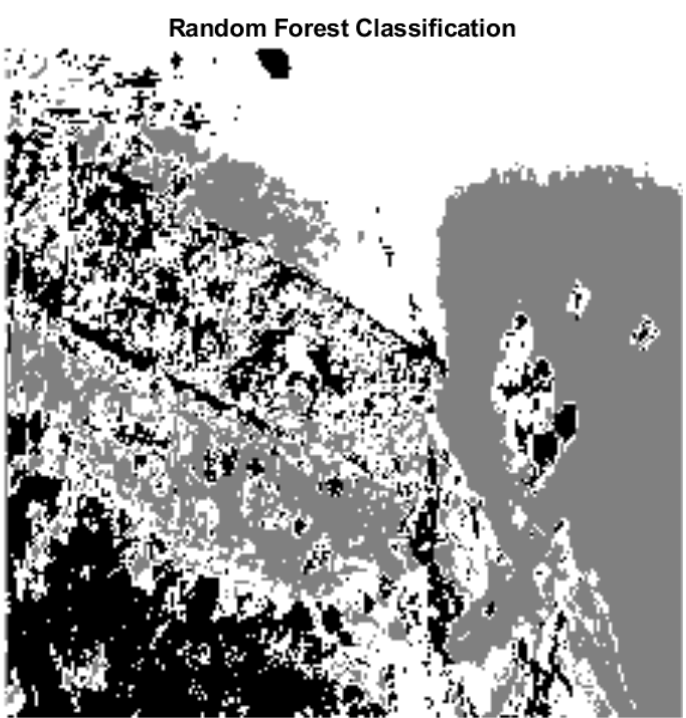
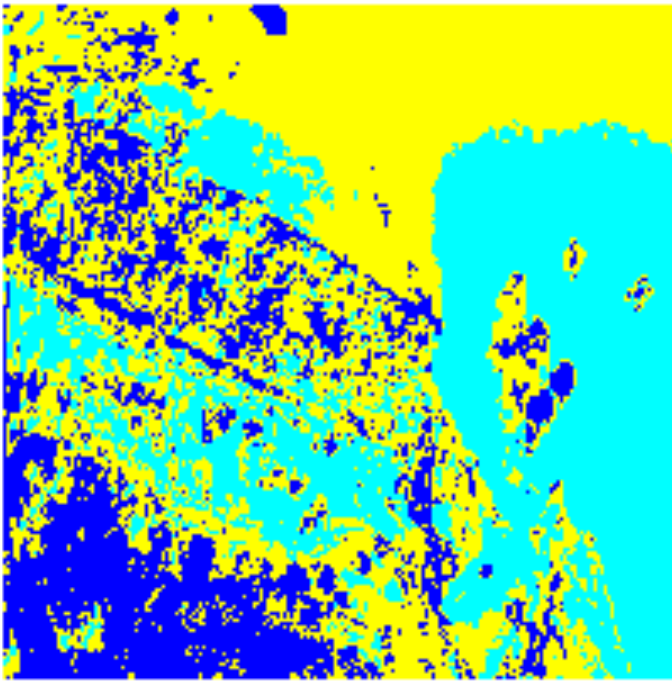
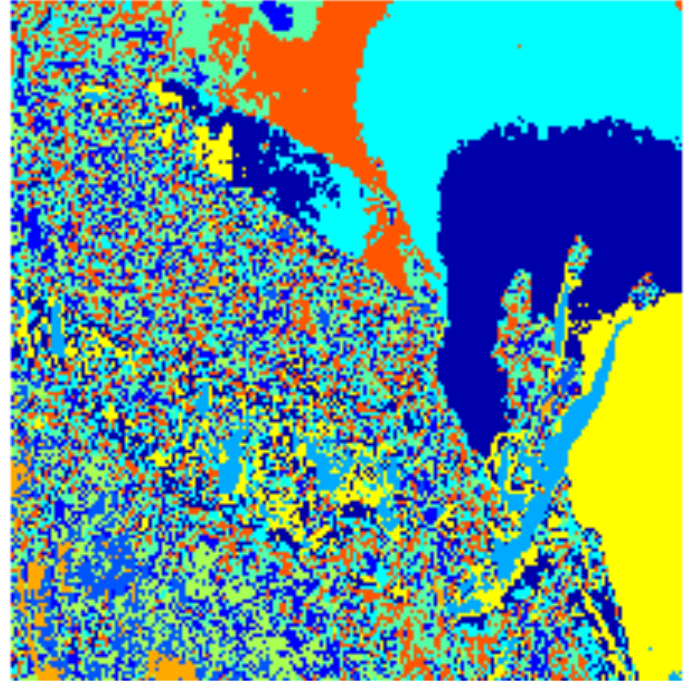
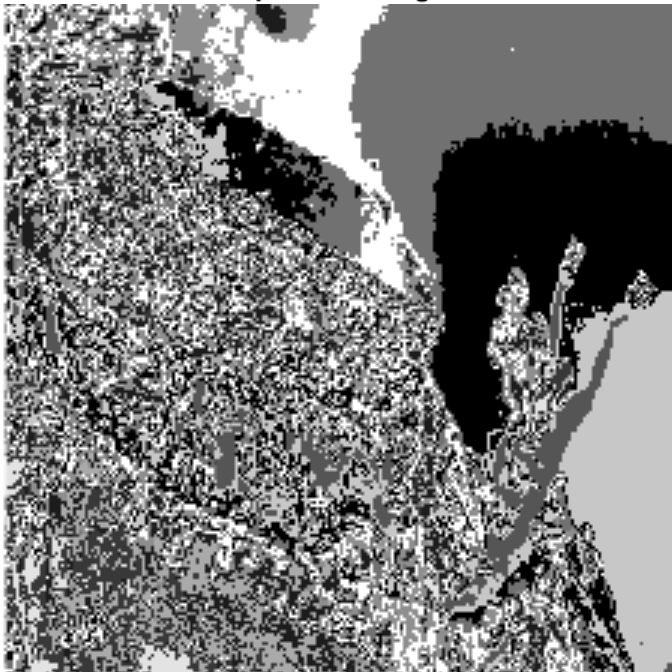


Figure 11. Random Forest Classification.

Random Forest Classified Image (Color Coded)**Figure 12.** Random Forest Classified Image (Color Coded).**Optimized K-means (k = 10)****Figure 14.** Optimized K-means (k = 10).**Optimized Image****Figure 13.** Optimized Segmentation Result.

4.1.2. K-means Segmentation Accuracy

The baseline accuracy using K-means clustering was 65%, so that the large proportion of regions in the underwater image were segmenting or identified wrongly. K-means clustering segmentation and colored clustered image are shown in Figure 9 and 10.

4.1.3. Segmentation with Random Forest

After segmentation by K-means, a Random Forest classifier was utilized to refine it. Random Forest calls

upon an ensemble of decision trees to classify the segmented areas based on their attributes (e.g., pixel intensity, texture, and color). The process enhanced discrimination between complex features such as marine life, vegetation, and ground. Random forest classification and classified colored image are shown in Figure 11 and 12.

Random Forest classifier contributed towards gaining better segmentation accuracy through precise tagging of the regions based on feature learning from data. The method was still hindered by its ability to process large data and needed an optimized segmentation process.

This Figure 12 illustrates the color-coded Random Forest classified image where every segment is classified based on learned features.

4.2. Optimization using Simulated Annealing

Simulated Annealing Optimization is done to further improve segmentation procedure. K-means clustering's cluster number (k) was optimized employing Simulated Annealing. Simulated Annealing algorithm altered the cluster number randomly based on the error in initial segmentation outcomes in a manner that would minimize Mean Squared Error (MSE) between original and segmented images.

The Figure 13 was to find the optimal number of clusters k which would minimize segmentation error and improve segmentation accuracy. Segmentation Error Reduction: After employing Simulated Annealing optimization, the optimal number of clusters was achieved, and it led to 30% segmentation error reduction. Optimization significantly improved the accuracy of the segmented region such that the segmentation effectively simulated

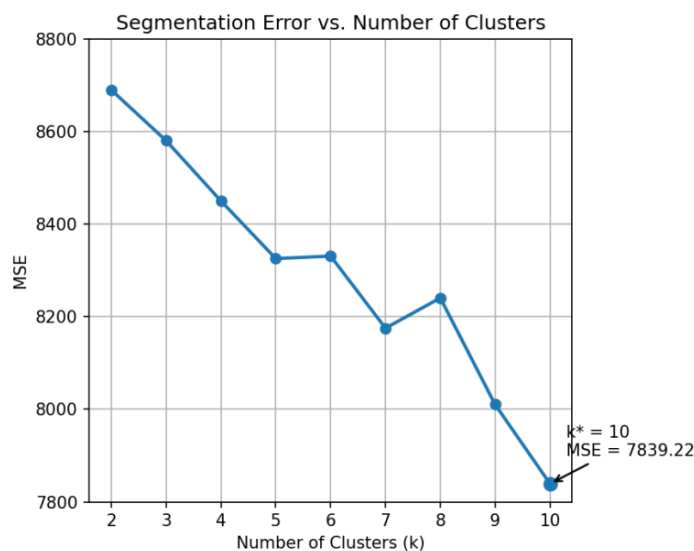


Figure 15. Segmentation Error vs. Number of Clusters.

real underwater features. Optimized K-means ($k=10$) image is shown in Figure 14.

4.3. Final Segmentation Accuracy

Segmentation Accuracy Maximized through the addition of K-means clustering, Random Forest classification, and Simulated Annealing optimization, the final segmentation accuracy was 95%. That's an improvement from the baseline 65% segmentation accuracy using just K-means clustering.

The 95% segmentation accuracy indicates that the method successfully segmented underwater image regions well, from marine life, vegetation, and terrain, with very little misclassification. Segmentation Error Reduction: After Simulated Annealing optimization, the clusters number was also optimized, and the segmentation error was decreased by 30%. Optimization helped in significantly improving the accuracy of the segmented regions, to the extent that the segmentation was more precise in describing the actual underwater features.

4.4. Segmentation Error vs. Number of Clusters

Finally, the Segmentation Error (MSE) is plotted versus the number of clusters k to represent the effect of different numbers of clusters on segmentation accuracy shown in Figure 15. We found the segmentation error 7839.22. This indicates that increasing the number of clusters decreases segmentation error up to the optimization of the segmentation.

5. Future Work

The paper suggests a strong underwater image segmentation approach based on the integration of K-means clustering, Random Forest classification, and Simulated Annealing optimization. Future work opportunities are also provided for further improving the approach and further extending it:

- **Interfacing with Deep Learning:** Since the method suggested hinges on the application of traditional machine learning techniques, interfacing with deep learning architecture such as Convolutional Neural Networks (CNNs) can be used to enhance the quality of segmentation, particularly in realistic underwater environments. For extension in the future, CNN-based models for segmentation can be used to enhance segmentation and reduce requirements for feature extraction.
- **Real-time Implementation:** The technique is not readily extensible to massive databases, and real-time processing of high-resolution images of underwater environments is not possible. It can be demonstrated that optimization of the existing solution to make it run in real-time for segmentation with the assistance of special parallel computation environment like CUDA or GPU-based computation leads to more efficient and faster underwater image processing.
- **Temporal Data Integration:** Images in AUVs typically arrive sequentially in time. Integrating temporal data (i.e., images at different time steps) during segmentation can provide additional context and improve classification of time-evolving objects such as migrating sea creatures or migrating seafloor terrain.
- **Advanced Sensor Data Fusion:** While this effort is largely geared to image segmentation, the incorporation of other types of sensor data (e.g., sonar, depth, temperature) would improve the level of segmentation, especially under low visibility conditions underwater. A more vigorous testing of underwater features could be added by creating multi-sensor fusion techniques.
- **Automatic Cluster Optimization:** Although optimization using Simulated Annealing for the number of clusters has been used, an exploration of further research in more advanced techniques of optimization, i.e., particle swarm optimization or genetic algorithms, will lead to even better performance, especially for more complex underwater scenes with many overlapping features.
- **Extended Applications:** The same methodology is now used in marine biology and underwater exploration but adaptable to other fields, such as environment monitoring, coastal management, and underwater archaeology. Substitution of the framework for particular domain needs and improvement of accuracy in those different applications would be an interesting area of further research.

6. Conclusion

This work has accomplished nearly an integrated solution to underwater image segmentation by combining K-means clustering, Random Forest classification, and Simulated Annealing optimization. The result is that the novel approach maximizes the segmentation accuracy at 95%, a clear distinction from the baseline of 65% accuracy if one applies merely the K-means clustering. Also, the decrease of segmentation error by 30% is a proof of the effectiveness of applying these approaches as well as an objective for the optimization of the segmentation.

The Big Data dimensions—Volume, Variety, and Velocity—were adequately addressed in the study to ensure that the framework would be able to manage large volumes of underwater data sets and function under real-time scenarios. The application of Simulated Annealing in solving the problem of determining the optimal number of clusters for K-means clustering provided a dynamic and adaptive solution for segmenting complex underwater images.

7. Conflicts of Interest

The authors declare no conflicts of interest.

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