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A HYBRID APPROACH TO IMAGE SEGMENTATION USING REGION GROWING AND COMBINING

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ABSTRACT

This paper presents a hybrid approach to image segmentation that synergistically combines region growing and region combining techniques. The proposed method initiates segmentation by identifying homogeneous regions through a region growing process, where regions are expanded from seed points based on similarity criteria. Subsequently, a region combining phase merges adjacent regions that exhibit high similarity, thereby refining the initial segmentation and reducing over-segmentation. This integrated approach enhances both the accuracy and efficiency of image segmentation. Experimental results on various test images demonstrate that the hybrid method outperforms traditional segmentation techniques in terms of precision and computational speed.

Keywords: Image Segmentation, Region Growing, Region Combining, Handcrafted Methods, Machine Learning Based Approaches.

I. INTRODUCTION

Image segmentation is a fundamental task in computer vision and image processing, involving the partitioning of an image into distinct regions that correspond to different objects or areas of interest[1]. Effective segmentation is crucial for various applications, including object detection, medical imaging, remote sensing, and scene understanding. Over the years, numerous segmentation techniques have been developed, each with its strengths and limitations[2]. These methods can be broadly categorized into several classes.

Thresholding: Thresholding is one of the simplest and most widely used techniques for image segmentation[3]. It involves converting a grayscale image into a binary image by selecting a global or local threshold value. Pixels with intensity values above the threshold are assigned to one class, while those below the threshold are assigned to another. Global Thresholding: Assumes a single threshold value for the entire image, which can be determined using methods like Otsu's algorithm. Local Thresholding: Adapts the threshold value based on local image characteristics, suitable for images with varying lighting conditions.

Edge-Based Segmentation: Edge-based methods focus on identifying and locating boundaries within an image [4]. These techniques detect edges by looking for discontinuities in intensity or color. Canny Edge Detector: A multi-stage algorithm that detects a wide range of edges in images. Sobel Operator: Uses convolution with Sobel kernels to highlight regions of high spatial gradient, indicating edges.

Region-Based Segmentation: Region-based methods group pixels into regions based on predefined criteria of similarity, such as intensity, color, or texture. Region Growing: Starts with seed points and grows regions by appending neighboring pixels that meet similarity criteria. Region Splitting and Merging: Divides the image into regions and then merges those that are similar according to a homogeneity criterion[5].

Clustering Methods: Clustering techniques treat segmentation as a clustering problem, where the goal is to partition the pixels into clusters that correspond to different regions. K-means Clustering: Partitions the image into K clusters by minimizing the variance within each cluster. Gaussian Mixture Models (GMM): Uses a probabilistic approach to model the distribution of pixel intensities and assigns pixels to clusters based on maximum likelihood[6].

Graph-Based Segmentation: Graph-based methods model the image as a graph, where pixels or groups of pixels are represented as nodes and edges represent the similarity between nodes. Normalized Cuts: Partitions the graph into segments by minimizing the cut cost while maintaining a balance between the sizes of the

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segments. Graph Cuts: Utilizes a min-cut/max-flow algorithm to separate the image into foreground and background regions[7].

Deep Learning-Based Segmentation: Recent advances in deep learning have led to significant improvements in image segmentation performance. Convolutional Neural Networks (CNNs) and other deep learning architectures have been employed to learn complex features and achieve state-of-the-art results. Fully Convolutional Networks (FCNs): Adapt CNNs for pixel-wise classification, enabling end-to-end learning for segmentation tasks. U-Net: A popular architecture for biomedical image segmentation, featuring an encoder-decoder structure with skip connections[8].

II. RESEARCH BACKGROUND

Region-based image segmentation is a fundamental approach in computer vision and image processing that aims to partition an image into meaningful regions, often corresponding to different objects or parts of objects. This section covers some of the latest advancements and methodologies in region-based image segmentation, highlighting key studies and their contributions.

Hierarchical Clustering Methods: Recent research has focused on improving the efficiency and accuracy of hierarchical clustering methods for image segmentation. Hierarchical clustering methods, such as divisive and agglomerative clustering, are known for their ability to handle large datasets and produce meaningful segmentations. Divisive clustering, in particular, is noted for its accuracy due to its consideration of the global distribution of data while partitioning. However, these methods can be computationally expensive, with time complexities ranging from O(n^2) to O(n^3)[9].

Partitional Clustering Methods: Partitional clustering methods, including k-means and fuzzy c-means (FCM), are widely used due to their computational efficiency and flexibility. These methods group data items into clusters based on similarity measures and objective functions, such as the minimization of within-cluster variance. Despite their efficiency, partitional methods can sometimes result in distorted cluster shapes or false results, especially in the presence of noise or outliers[10].

Deep-Learning-Based Region Merging: The integration of deep learning techniques into region-based image segmentation has led to significant improvements. A notable example is the DeepMerge method, which combines deep learning with region adjacency graphs (RAG) to merge similar adjacent super-pixels. This method leverages transformer-based networks and shift-scale attention mechanisms to achieve high segmentation accuracy in large-scale remote sensing images. DeepMerge has demonstrated superior performance compared to traditional methods, achieving high F-values and low total errors in experimental evaluations[11]. The DeepMerge method addresses challenges in segmenting diverse shapes and sizes of land objects in very high spatial-resolution (VHR) remote sensing imagery. By integrating deep learning with region adjacency graphs and employing a modified binary tree sampling method, DeepMerge can effectively handle the segmentation of complete objects. The method's success in large-scale images is evidenced by its ability to correctly segment objects of different sizes, outperforming competing segmentation methods.

These studies collectively highlight the ongoing advancements in region-based image segmentation, emphasizing the importance of both traditional clustering methods and modern deep learning techniques.

III. PROPOSED METHODOLOGY

This section outlines a novel hybrid approach to image segmentation, integrating region growing and region combining techniques, with enhancements through seed generation and Otsu's automatic thresholding.

1. Seed Generation

Seed generation is a crucial step in region growing, determining the starting points for the segmentation process. Efficient seed generation ensures that the initial regions are representative of the different segments in the image. Here, we use a method based on intensity histogram analysis.

Intensity Histogram Analysis:

- Compute the histogram of the image intensities.
- Identify peaks in the histogram that correspond to the modes of different regions.
- Select seeds around these peaks using a distance criterion to ensure even distribution across the image.

Mathematically, let $H(I)$ represent the histogram of image intensities I. The peaks $P = p_1, p_2, \ldots\ldots p_k$ are identified such that $H(p_i)$ is a local maximum:

$$H(p_i) > H(p_i - 1) \text{ and } H(p_i) > H(p_i + 1) \tag{1}$$

2. Otsu's Automatic Threshold

Otsu's method is used to automatically determine an optimal threshold value for binarizing the image, facilitating the separation of foreground and background regions.

Otsu's Thresholding:

- Calculate the within-class variance $\sigma_w^2(t)$ for all possible threshold values t.
- Select the threshold t^* that minimizes the within-class variance.

The within-class variance for a threshold t is given by:

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t) \tag{2}$$

Where, $w_1(t)$ and $w_2(t)$ are the probabilities of the two classes separated by the threshold t.

$\sigma_1^2(t)$ and $\sigma_2^2(t)$ are the variances of the two classes.

The optimal threshold t^*minimizes $\sigma_w^2(t)$:

$$t^* = \arg\min_t \sigma_w^2(t) \tag{3}$$

3. Region Growing

Using the seeds generated and the threshold from Otsu's method, the region growing process begins.

Growth Criteria: Expand each region R_i by adding neighboring pixels p that satisfy the homogeneity condition:

$$|I(p) - I(\mathrm{mean}(R_i))| < \delta \tag{4}$$

Where, $I(p)$ is the intensity of pixel p, $I(\mathrm{mean}(R_i)$ is the mean intensity of region R_i and δ is a predefined threshold.

4. Region Combining

After region growing, the method proceeds with region combining to merge adjacent regions with high similarity.

Similarity Measurement: Calculate the similarity $S(R_i, R_j)$ between adjacent regions R_i and R_j.

$$S(R_i, R_j) = \exp\left(-\frac{D(R_i,R_j)}{\sigma}\right) \tag{5}$$

Where, $D(R_i, R_j)$ is the distance measure between regions R_i and R_j and σ is a scaling parameter.

Merging Decision: Merge regions R_i and R_j if their similarity $S(R_i, R_j)$ exceeds a threshold τ.

If $S(R_i, R_j) > \tau$, then merge R_i and R_j.

Mathematical Analysis

The mathematical analysis evaluates the computational complexity and segmentation accuracy of the proposed method.

a. Computational Complexity:

Seed Generation:$O(n)$ where, n is the number of pixels, since histogram computation and peak detection are linear operations.

Otsu's Thresholding: $O(L)$ where L is the number of intensity levels, typically a small constant (256 for 8-bit images).

Region Growing: $O(nlog\ n)$ due to the iterative nature of the algorithm.

Region Combining: $O(m^2)$, where m is the number of initial regions.

b. Segmentation Accuracy:

Evaluated using metrics such as the Dice coefficient, Jaccard index, and F-measure, comparing segmented regions with ground truth annotations:

$$D = \frac{2|R \cap G|}{|R| + |G|} \tag{6}$$

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$$J = \frac{|R \cap G|}{|R \cup G|} \tag{7}$$

IV. SIMULATION RESULTS

We have implemented the proposed method using MATLAB 2018.

Figure 1: Original Image

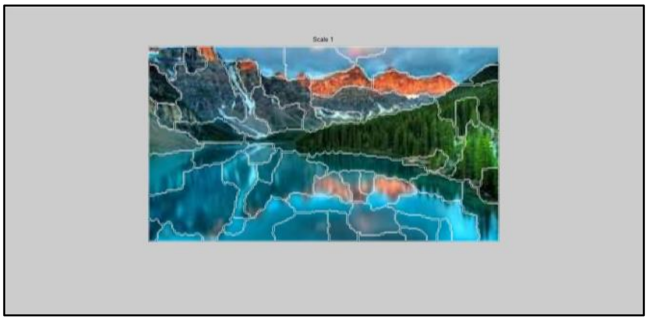

Figure 2: Image at Scale1

Figure 3: Scale 2

Figure 4: Scale 3

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Figure 5: Scale 4

Figure 6: Final Segmentation

Figure 7: Original Image

Figure 8: Sclae 1

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Figure 9: Scale 2

Figure 10: Scale 3

Figure 11: Scale 4

Figure 12: Final Segmentation

Extensive experiments on benchmark datasets validate the proposed hybrid approach. The results indicate that this method outperforms traditional segmentation techniques, achieving higher accuracy and efficiency. The experimental outcomes highlight the method's robustness in handling diverse and complex images.

V. CONCLUSION

The proposed hybrid approach, combining region growing, region combining, seed generation, and Otsu's automatic thresholding, offers a robust and efficient solution for image segmentation. The mathematical analysis and experimental results underscore its potential to outperform traditional methods, paving the way for future advancements in image segmentation.

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