AEIJMR – Vol 13 – Issue 09 – September 2025 ISSN - 2348 – 6724

An Efficient Hybrid Image Segmentation Approach Using Watershed and Breadth-First Search for Over-Segmentation Reduction

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Abstract

Image segmentation is a critical process in image analysis and computer vision, essential for object recognition, scene understanding, and medical diagnostics. Despite numerous segmentation techniques, over-segmentation remains a significant challenge, particularly in watershed-based methods, where images are divided into excessive, fragmented regions. This paper presents a simple yet effective hybrid segmentation approach that integrates watershed transformation with a breadth-first search (BFS) based region merging technique. The watershed algorithm provides initial segmentation, while BFS groups neighbouring regions based on similarity in intensity and texture, evaluated via statistical measures like standard deviation. Experimental results on standard test images demonstrate that this approach significantly reduces over-segmentation, achieving improved homogeneity while preserving key boundaries. The method is computationally efficient, adaptable, and suitable for real-world image analysis tasks.

Keywords

Image segmentation, Watershed algorithm, Breadth-first search, Over-segmentation, Region merging, Statistical similarity, Image processing.

1. Introduction

Image segmentation involves partitioning an image into meaningful regions representing objects, structures, or backgrounds. It serves as a foundational step for higher-level image interpretation tasks such as object recognition, tracking, and medical diagnosis.

A variety of segmentation methods have been developed, including thresholding, clustering, edge detection, region growing, and graph-based approaches. Among them, the watershed algorithm, inspired by topographical watershed lines, is highly effective at detecting object boundaries. However, it often creates excessively fragmented partitions known as over-segmentation, especially in noisy images or complex scenes.

To tackle this issue, post-processing steps like region merging are essential. This paper proposes a hybrid approach combining watershed segmentation with a breadth-first search technique guided by statistical similarity to merge adjacent regions. The merging criterion employs standard deviation-based measures to ensure regions are combined only when homogeneous.

The proposed approach balances effectiveness and simplicity, making it viable for various imaging applications where robust segmentation is required without excessive computation.

2. Objectives

- Develop a segmentation framework combining watershed partitioning with BFS-based region merging.
- Utilize statistical measures (e.g., standard deviation) to determine similarity for merging.
- Reduce over-segmentation while preserving important boundaries.
- Validate performance on benchmark natural images.
- Demonstrate method efficiency and ease of implementation.
- Compare results with traditional segmentation methods showing improvements.

3. Literature Review

Watershed Segmentation

The watershed algorithm interprets grayscale images as landscapes where watersheds delimit catchment basins. While it accurately detects edges, its sensitivity to small intensity variations causes over-segmentation.

Region Merging

Techniques that merge adjacent similar regions have been developed to counter over-segmentation. Statistical criteria based on texture, intensity, or color guide the merging process to unify fragmented areas.

Breadth-First Search

BFS efficiently explores adjacent regions in a graph representation of segmented images, enabling systematic merging based on predefined criteria.

Other Methods

Clustering methods like k-means and fuzzy c-means improve segmentation via pixel grouping but often rely on good initialization and may not preserve boundaries well.

4. Methodology

4.1 Initial Segmentation: Watershed

- Compute image gradient magnitude using differential operators (e.g., Sobel).
- Apply watershed transform to segment image into initial regions based on topographical features.
- Result is a set of fragmented regions due to over-segmentation.

4.2 Region Merging: Breadth-First Search

4.2.1 Region Adjacency Graph Construction

- Each segmented region is a node, edges connect adjacent regions.

4.2.2 Statistical Similarity Evaluation

- Calculate mean (μ\muμ) and standard deviation (σ\sigmaσ) of intensities for each region.
- Two regions RiR_iRi and RjR_jRj are candidates for merging if:

$$\frac{|\mu_i - \mu_j|}{\max(\sigma_i, \sigma_j)} < \text{Threshold}$$

4.2.3 BFS Merging Algorithm

- Initialize queue with all regions.
- For each region dequeued, examine neighbors.
- Merge neighbors meeting similarity criterion and update statistics.
- Repeat until no further merges are possible.

5. Algorithm

Input: Grayscale image III, Threshold TTT

Output: Segmented Regions

1. Compute gradient image G=∇IG = \nabla IG=∇I.
2. Apply watershed algorithm on GGG to get initial regions SSS.
3. Build adjacency graph Ga=(V,E)G_a = (V, E)Ga=(V,E) from SSS.
4. Compute mean and standard deviation for each region in VVV.
5. Initialize BFS queue Q=VQ = VQ=V.
6. While QQQ not empty:
   - Dequeue region r.
   - For each neighbor n of r, if $\frac{|\mu_r - \mu_n|}{\max(\sigma_r, \sigma_n)} < T$, merge r and n:
     - Update adjacency graph and statistics.
     - Enqueue merged region.
7. Return merged segmentation map.

6. Implementation Details

- Developed in Python with OpenCV for watershed and NumPy for processing.
- Input images resized to 256×256 for uniformity.
- Gradient computed using Sobel operator.
- Threshold TTT empirically set to 0.5 based on experiments.
- Merging iterates until no pairs satisfy similarity.
- Segmented results visualized and saved for inspection.

7. Results and Analysis

7.1 Dataset

Tested on standard natural images such as “Boat,” “Flower,” “Butterfly,” and “Bird.”

7.2 Quantitative Results

Image	Initial Regions	Final Regions	Reduction (%)	Mean Std Dev
Flower	245	140	42.86	0.2293
Boat	310	180	41.94	0.2484
Butterfly	280	165	41.07	0.2817
Bird	260	155	40.38	0.2769

7.3 Visual Evaluation

Figure 1 shows sample segmentations: original, watershed result (over-segmented), and final merged output. Merging reduces small fragmented regions, yielding coherent, natural segment boundaries.

7.4 Discussion

The approach reduces over-segmentation efficiently without predefined region numbers. Statistical similarity ensures only compatible merges, preserving edges. BFS enables systematic exploration, maintaining computational feasibility.

8. Conclusion

This paper introduced a simple hybrid method for image segmentation combining watershed transform with breadth-first search guided by statistical region similarity. The technique effectively reduces over-segmentation, improves region homogeneity, and preserves critical edges. Experiments on benchmark images demonstrate significant improvements over baseline watershed segmentation. The method’s simplicity and adaptability make it suitable for diverse image analysis applications. Future work includes extending the method to color and 3D images and integrating adaptive similarity measures.

9. References

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