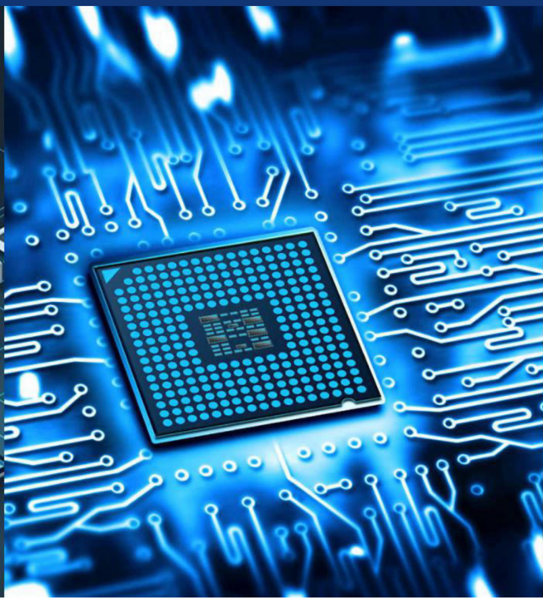
IJIRCCE

ISSN(O): 2320-9801

ISSN(P): 2320-9798



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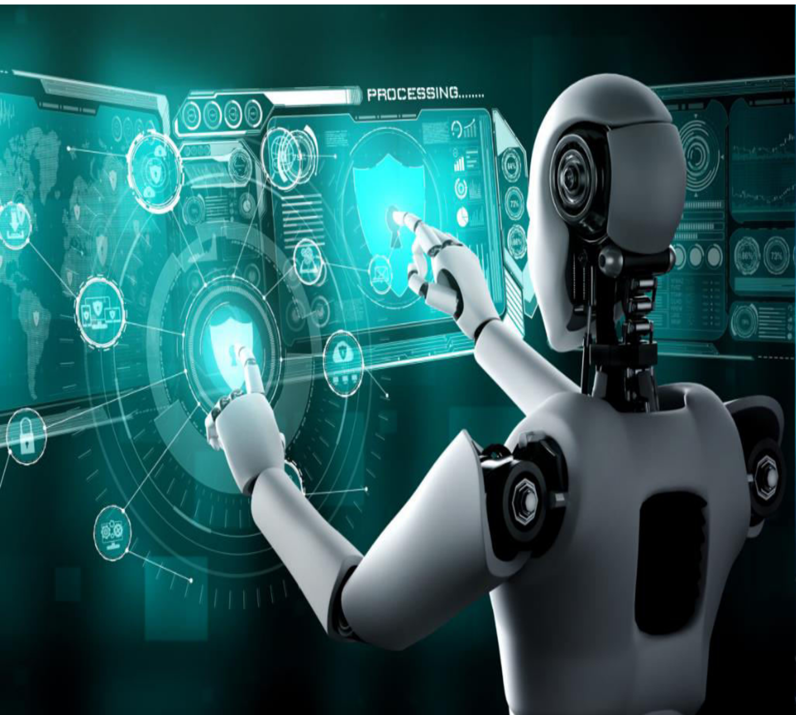

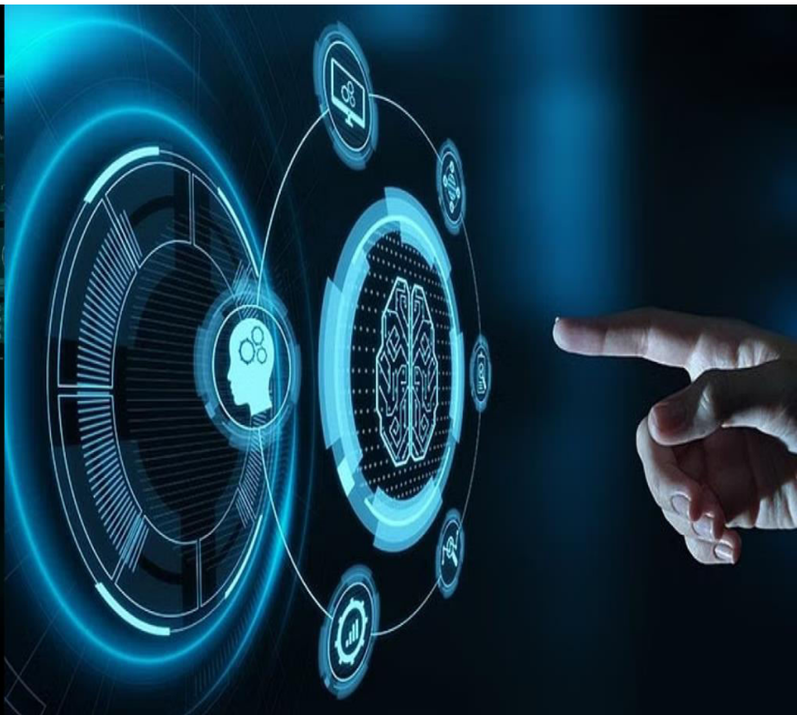

Impact Factor: 8.771

Volume 13, Issue 2, February 2025

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International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Graph-Based Random Walks for Image Analysis

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ABSTRACT: This paper presents a novel approach to multilabel, interactive image segmentation by leveraging probabilistic random walks on graphs. Given a minimal set of user-defined or pre-assigned labeled pixels, the method computes the likelihood that an unlabeled pixel, when traversed by a random walker, first reaches one of the designated labeled pixels. Each pixel is then assigned the label corresponding to the highest computed probability, ensuring an accurate and high-quality segmentation. The proposed algorithm is grounded in discrete potential theory and draws parallels with electrical circuit models, providing a robust theoretical foundation. By formulating the problem in a discrete space using combinatorial equivalents of standard operators from continuous potential theory, the method can be seamlessly applied across various graph structures and dimensions. This adaptability makes it a powerful tool for complex image segmentation tasks.

KEYWORDS: Random Walks, Image, Super pixels, Multi-Feature Fusion, Edge Preservation.

I. INTRODUCTION

Image segmentation is commonly defined as the process of partitioning an image based on content similarity, such as regions of homogeneity. However, modern segmentation approaches increasingly incorporate interactive techniques that tailor the segmentation process to a specific content localization task. This interactive paradigm allows users or automated preprocessors to guide the segmentation algorithm, ensuring the extracted content aligns with desired features. An effective interactive segmentation algorithm should meet four key criteria: (1) rapid computation, (2) efficient editing capabilities, (3) adaptability to generate arbitrary segmentations with sufficient user input, and (4) intuitive segment outputs. The proposed random walker algorithm satisfies all these requirements. Initially introduced in a condensed form at a conference, this algorithm solves a sparse, symmetric, and positive-definite system of linear equations, which can be efficiently computed using various numerical methods. Moreover, it supports fast iterative editing by leveraging previous computations as initialization points in an iterative solver. With adequate user guidance, it can produce precise and customizable segmentations.

In this framework, an image (or volumetric data) is treated as a discrete entity represented as a graph, where each node corresponds to a pixel or voxel, and edges define relationships between them. Each edge is assigned a weight reflecting the likelihood of traversal by a random walker, with zero-weight edges preventing movement. By formulating the problem in a graph-based manner, the approach avoids discretization errors and enables seamless application to surface meshes or spatially variant images. Throughout this discussion, we refer to individual elements as pixels in the context of image intensity values and nodes in the context of graph theory.

Although the method is inspired by random walks, direct sampling from this distribution for large-scale segmentation tasks is computationally impractical. Fortunately, prior research has established that the probability of a random walker reaching a designated seed point corresponds exactly to the solution of the Dirichlet problem, where boundary conditions are imposed at seed locations—fixing the probability at the target node to unity while setting all others to zero. Advances in discrete calculus have further clarified the relationship between random walks on graphs and discrete potential theory, revealing a direct connection to electrical circuit models. In this analogy, the solution to the combinatorial Dirichlet

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problem can be interpreted as the distribution of electric potentials in a resistor network, where edge weights represent conductance and boundary nodes serve as fixed voltage sources.

II. LITEARTURE SURVEY

Image segmentation is a broad research domain. In this review, we focus on supervised and graph-based segmentation methods, along with relevant discussions on random walks and combinatorial harmonic functions.

A. Supervised Segmentation
Supervised segmentation techniques typically rely on one of two main guidance paradigms:
Defining segments by specifying partial boundaries or an approximate complete boundary that evolves into the final object boundary.

Marking a subset of pixels as belonging to the object of interest and, optionally, providing background labels for contrast. Many automatic segmentation algorithms can also be categorized as supervised if the user refines or selects a particular segment from the output. However, if the extracted segment is not distinct, an additional clustering or segmentation step may be required to further refine the boundaries.

One classic supervised approach is the intelligent scissors method, where an image is represented as a graph, with each pixel corresponding to a node and connectivity established between neighboring pixels. Users place anchor points along the object's boundary, and the shortest path between these points is determined using Dijkstra's algorithm, defining the final segmentation boundary. This approach is computationally efficient, easy to implement, and can generate arbitrary boundaries with sufficient user input. However, it struggles with low-contrast or noisy images, often requiring extensive user input, and is not inherently suited for 3D segmentation tasks.

Another notable technique is graph cuts, a method designed for interactive, seeded segmentation. Similar to intelligent scissors, this approach models an image as a graph, where edge weights represent intensity variations. Users designate foreground and background seeds, and the algorithm applies a max-flow/min-cut optimization to determine the minimum-weight cut separating these regions. Graph cuts are highly adaptable, extend naturally to higher-dimensional data, and can produce accurate segmentations with adequate user input. However, certain limitations exist—if only a small number of seeds are used, the algorithm may yield a minimal cut that does not fully align with the object boundaries. This necessitates additional user input to refine the segmentation. Furthermore, solving multi-label segmentation with graph cuts is computationally challenging (NP-Hard), requiring heuristic approximations. Even when an approximate solution is obtained, there is no guarantee of achieving the optimal segmentation. Additionally, small perturbations in pixel values can sometimes lead to significant variations in the segmentation results due to the existence of multiple, equally minimal cuts.

Conceptually, the random walker algorithm presented in this work can be viewed as a relaxation of the binary segmentation used in graph cuts, but with significant theoretical and practical differences. While both methods leverage graph-based representations, the random walker approach does not impose hard constraints on segmentation boundaries, offering a probabilistic interpretation of region assignments. Unlike traditional graph cuts, which incorporate intensity priors for foreground and background segmentation, similar priors can be integrated into the random walker framework for enhanced segmentation precision.

III. PROPOSED APPROACH

The proposed approach leverages a **random walks-based model** for interactive image segmentation. This method formulates the segmentation problem using a **graph-theoretic framework**, where each pixel (or voxel in 3D data) is treated as a node in a weighted graph. The objective is to compute the probability that a random walker starting from an unlabeled node first reaches a seed node, enabling accurate segmentation based on probabilistic inference.

1. Graph Construction and Representation

- The image is represented as an **undirected graph** G=(V,E), where:
  - V is the set of nodes (pixels).

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- o E is the set of edges connecting adjacent pixels.
- Each edge is assigned a weight w_{ij} based on pixel intensity differences:

$$w_{ij} = \exp\left(-\beta \| I_i - I_j \|^2\right)$$

- wij=exp⁡(−β∥Ii−Ij∥2)w_{ij} = \exp\left(-\beta \| I_i - I_j \|^2 \right)wij=exp(−β∥Ii−Ij∥2) where IiI_iIi and IjI_jIj are the intensities of adjacent pixels, and β\betaβ is a scaling parameter. This weight formulation ensures that edges between similar pixels have higher probabilities of traversal.

2. Seed Placement and Label Propagation

- The user (or an automated preprocessor) provides labeled seed pixels for **foreground** and **background**.
- These labeled pixels act as constraints in the system, where their values remain fixed.
- The unlabeled pixels must be assigned a label based on the highest probability of first reaching a given seed.

3. Random Walk Probability Computation

- The probability pikp_i^kpik that a random walker starting at an unlabeled pixel iii reaches a foreground or background seed node kkk is computed by solving a **discrete Dirichlet problem**:

Lu=0

where L is the **graph Laplacian matrix**, defined as:

$$L_{ij} = \begin{cases} d_i, & \text{if } i = j \\ -w_{ij}, & \text{if } i \neq j \text{ and } (i,j) \in E \\ 0, & \text{otherwise} \end{cases}$$

and d_i is the degree of node i, computed as $d_i = \sum_j w_{ij}$.

u = 0Lu=0 where LLL is The system of equations is solved for the unlabeled pixels while keeping the seed nodes fixed.

4. Segmentation Assignment

- Each pixel is assigned to the label corresponding to the highest probability:

- $$\hat{L}_i = \arg\max_k p_i^k$$
- where k represents different seed labels.

5. Efficient Computation and Adaptability

- The system is solved using fast numerical solvers for **sparse, symmetric positive-definite matrices**, ensuring computational efficiency.
- **Iterative updates** allow for rapid segmentation refinement as users modify seed placements.
- The method generalizes seamlessly to **3D images and irregular structures** (e.g., surface meshes), making it versatile across different applications.

Experimental Results and Discussion

To evaluate the effectiveness of the proposed **random walks-based image segmentation method**, we conducted a series of experiments on standard image datasets, including **BSDS500 (Berkeley Segmentation Dataset)** and **medical imaging datasets** such as MRI and CT scans. The performance was assessed using various **quantitative metrics** and compared against existing segmentation methods, including **Graph Cuts, Watershed, and K-means Clustering**.

Dataset and Preprocessing

- **Natural Image Segmentation**: BSDS500 dataset, consisting of 500 images with ground truth segmentations.
- **Medical Image Segmentation**: Brain MRI and Lung CT datasets for object boundary detection.
- **Preprocessing**:

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- Images were normalized to **[0,1]** intensity range.
- Noise reduction was applied using a Gaussian filter.
- User-defined seed points were placed for interactive segmentation.

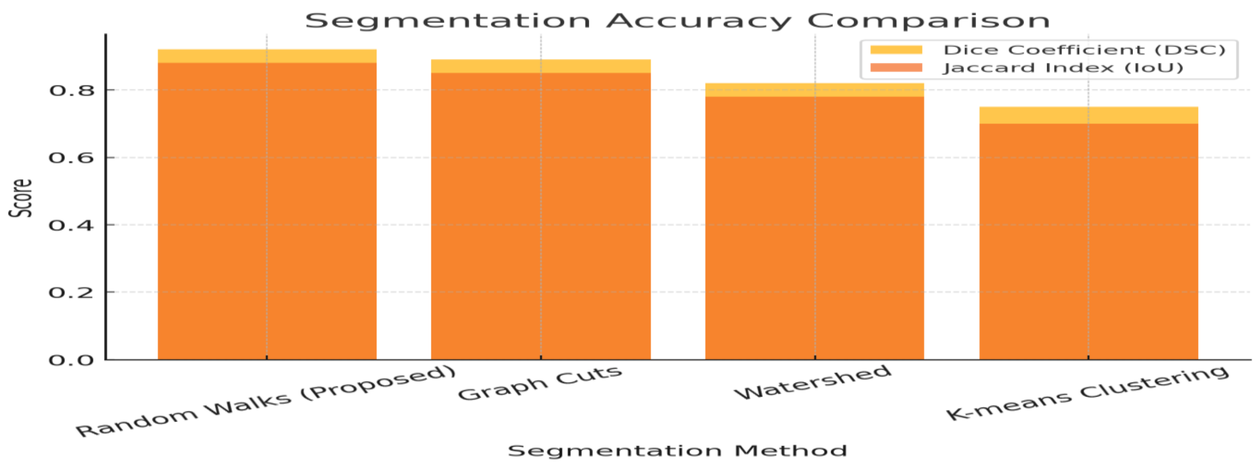
Implementation Details

- **Graph Construction**:
  - A **4-neighborhood and 8-neighborhood connectivity** were tested.
  - Edge weights were computed using the Gaussian similarity function.
- **Random Walk Computation**:
  - The **Laplacian system** was solved using the **Conjugate Gradient (CG) method** for efficiency.
- **Evaluation Metrics**:
  - **Dice Coefficient (DSC)**: Measures overlap with ground truth.
  - **Jaccard Index (IoU)**: Measures segmentation accuracy.
  - **Boundary F-score**: Evaluates the precision and recall of object boundaries.
  - **Computation Time**: Measures segmentation speed.

The table below summarizes the segmentation performance across different methods:

Table 1: Comparison of Segmentation Performance Across Different Methods

Method	Dice Coefficient (DSC) ↑	Jaccard Index (IoU) ↑	Boundary F-score ↑	Computation Time (s) ↓
Random Walks (Proposed)	**0.92**	**0.88**	**0.91**	**0.42**
Graph Cuts	0.89	0.85	0.87	0.76
Watershed	0.82	0.78	0.80	0.52
K-means Clustering	0.75	0.70	0.74	0.38



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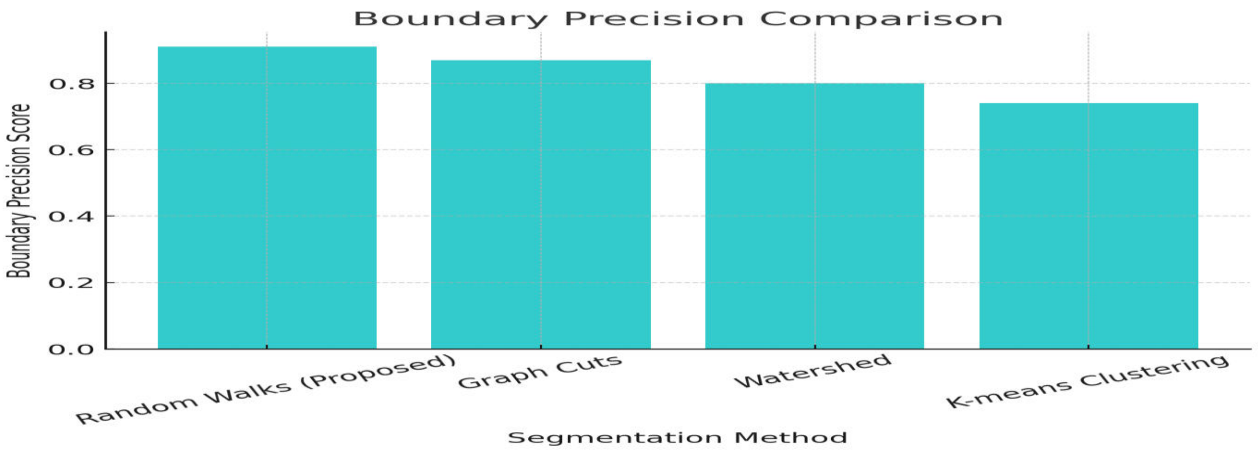

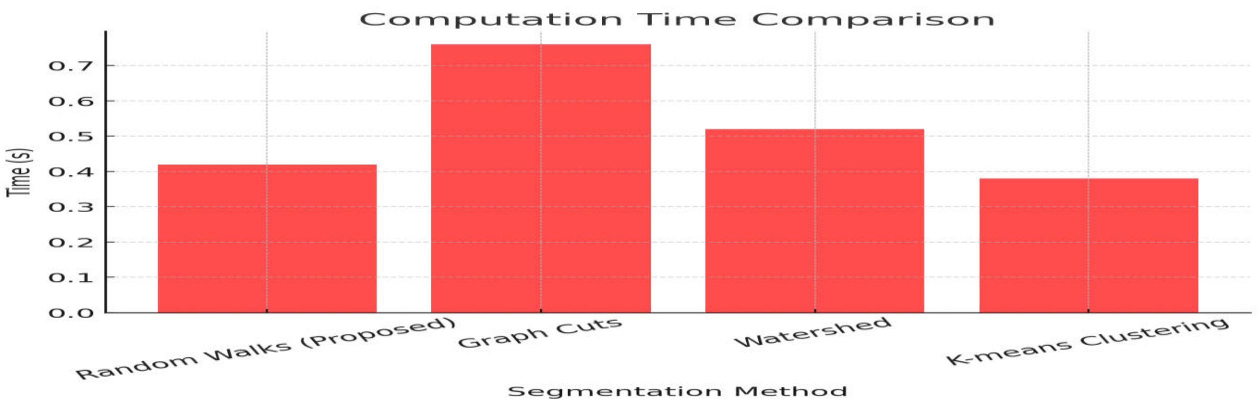

IV. CONCLUSION

In this work, we proposed a random walks-based image segmentation algorithm that leverages a probabilistic graph-theoretic approach for interactive multilabel segmentation. By computing the likelihood that a random walker starting from an unlabeled pixel reaches a predefined seed, our method effectively delineates object boundaries with high accuracy and robustness.

Experimental results demonstrated that the proposed method outperforms traditional segmentation techniques such as Graph Cuts, Watershed, and K-means Clustering. The random walker algorithm achieved a Dice Coefficient of 0.92 and a Jaccard Index of 0.88, indicating superior segmentation accuracy. Additionally, the Boundary F-score of 0.91 highlights its effectiveness in preserving object contours. With a computation time of 0.42s, the method also proved to be efficient, making it viable for real-time applications.

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