A Novel Approach to Segmenting Images of Paralysis-Affected Individuals Using GrabCut

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Abstract
In medical image analysis and diagnostics, segmentation of images is essential, especially for disorders like paralysis where localized image features can indicate the degree of damage. In this work, we use a dataset of patient visuals with paralysis to isolate and highlight areas that are impaired using the GrabCut image segmentation technique. With little assistance from the user, GrabCut, a semi-automatic segmentation technique based on Gaussian Mixture Models (GMMs) and repeated graph cuts, is quite effective in removing foreground objects from complicated backgrounds. A individual dataset made up of images of the hands and leg of patients with partial paralysis was used to test the recommended method. GrabCut performs better than conventional methods in terms of accuracy and visual quality when compared to common segmentation algorithms like K-means clustering and Otsu's thresholding.

Keywords: GrabCut, Image Segmentation, Paralysis, Medical Imaging, Gaussian Mixture Model, Foreground Extraction, Semi-Automatic Segmentation

1. INTRODUCTION

A health-related ailment identified as paralysis, which often comes on by stroke, spinal cord injury, or neurological illnesses, is characterized by the partial or total loss of muscle function in one or more body parts. The use of image-based evaluations, such as the examination of skin texture, limb posture, or face symmetry, is growing in both early detection and rehabilitation planning. Clinicians can measure the degree of impairment and track improvement over time by properly segmenting the impacted areas in medical pictures.

When applied to datasets of patients with paralysis, traditional segmentation techniques like thresholding or clustering-based methods frequently fail because of issues like: • uneven lighting; • low contrast between healthy and affected tissue; • imaging device noise and artifacts; and • complicated anatomical boundaries.

On the other hand, by simulating pixel distributions and spatial continuity, graph-based techniques like GrabCut offer reliable segmentation. This study examines GrabCut's potential for segmenting medical photos of individuals with paralysis and evaluates how well it performs in comparison to traditional techniques.

This study investigates the use of the GrabCut image segmentation method, an interactive foreground extraction methodology based on graph cuts and energy reduction, to successfully segment medical photographs of patients who have paralysis in order to address these issues. Because of its reputation for combining color and edge information, GrabCut is especially well-suited for segmenting areas with faint borders, which is frequently the case in medical scans of paralyzed muscles or limbs.

1.1 Why GrabCut for Paralysis-Affected Image Segmentation?

In this situation, GrabCut's main benefit is its capacity to iteratively optimize the segmentation mask even with very little initial user input (such as a bounding box surrounding the region of interest). This technique makes it possible to distinguish between functional and non-functional areas more clearly in photos of people who have paralysis, where atrophy or a lack of movement may cause some areas to appear visually similar. This is particularly crucial in cases of

- facial paralysis, where it is necessary to measure muscle asymmetry.
- Limb paralysis, when it's important to distinguish between affected and unaffected parts.
- Thermal imaging, in which variations in skin temperature indicate activity in the muscles or nerves.

1.2 Objectives of This Study

This study aims to:

- Demonstrate the potential of GrabCut as a preprocessing step for additional analysis such as region classification, nerve mapping, or treatment tracking.
- Perform the GrabCut segmentation method on a carefully selected dataset of images from patients who have paralysis.
- Quantitatively evaluate the segmentation quality using metrics like the Dice score and Jaccard index.
- Compare GrabCut's performance with more conventional segmentation techniques like Otsu Thresholding and K-means Clustering.

2. LITERATURE REVIEW

Over the past few decades, many algorithms have been developed for medical image segmentation, which has been the subject of much research. Otsu's method, a popular global thresholding technique, uses histogram analysis to distinguish between foreground and background. Despite being computationally efficient, it frequently fails in photos when the brightness of the pixels overlap. By assembling pixels into clusters according to color similarity or intensity, K-means clustering divides images into segments. Although helpful, it lacks geographical context and frequently leads to erroneous or fragmented segmentation in medical settings.

For interactive image segmentation, GrabCut, first presented by Rother et al. (2004), combines graph cuts with GMMs. The foreground and background models must be initialized using a bounding box input. The segmentation is improved in later iterations by using edge potentials and color distributions. Recent research has demonstrated its efficacy in a range of biomedical applications.

Higher segmentation accuracy and processing time in natural and biological pictures were demonstrated by Pang et al. (2024) using an updated GrabCut method with improved boundary refining. In order to segment dermoscopic skin lesions, Jaisakthi et al. (2018) used GrabCut in combination with K-means clustering. This allowed for efficient boundary identification, especially in low-contrast pictures. In order to detect coronary calcium deposits, Lee et al. (2023) implemented GrabCut as a post-processing step after K-means clustering in cardiac CT image segmentation. Similar to this, a 2024 study that showed promise therapeutic relevance combined GrabCut for tumor border refining and YOLOv7 for object detection in brain MRI images. The study was published in Frontiers in Oncology.

For dental X-ray image segmentation, Mao et al. (2018) used a modified GrabCut technique, customizing it to the difficulties of grayscale medical imaging with overlapping anatomical components. The segmentation of limb and facial images in paralysis evaluation is directly related to this work.
Wang et al. (2022) presented a hybrid method that combines neural network refinement with initial bounding box input to replicate the GrabCut process using a deep CNN framework (BIFSeg). The synergy between traditional methods and deep models was demonstrated by Fu et al. (2016), who similarly combined deep learning with graph-cut principles to produce entirely autonomous figure-ground segmentation.
In order to support automated diagnosis methods, Nandyal and Kausar (2024) have created a database of paralyzed patients. This work is especially relevant to this study because it provides information and context for practical validation and supports the use of image segmentation techniques (such as the GrabCut method) in clinical datasets related to paralysis.

3. METHODOLOGY

3.1 Dataset Description

The study's dataset consists of number of color image dataset of people with paralysis, including pictures of their arms and legs. Every image dataset has a 512x512 pixel resolution and was taken in a controlled lighting environment. For performance evaluation, skilled radiologists developed ground truth segmentation masks.

3.2 GrabCut Algorithm

GrabCut is a semi-automated segmentation method that uses graph cuts to minimize energy. It achieves precise foreground-background separation by combining optimization and statistical modeling. The algorithm starts by enclosing the object of interest in a user-defined bounding box. The area outside the box is regarded as the background, and the area inside the box is regarded as the likely foreground.
A Gaussian Mixture Model (GMM) is used to model each pixel, estimating the probability distribution of pixel intensities for both the background and the foreground areas. An energy function's data terms are assigned using these probabilities. In order to model the smoothness term, a neighborhood system is also developed, which guarantees that nearby pixels with comparable intensities are probably located in the same area.
The overall energy function is defined as:

$$E(L, \theta, z) = U(L, \theta, z) + V(L, z)$$

Where:

- L represents the label assignment of pixels (foreground or background)
- θ are the GMM parameters
- z are the image pixel values
- U is the data term based on GMM likelihoods
- V is the smoothness term encouraging similar labels for neighboring pixels

On a graph where pixels represent nodes and edges encode both data fidelity and smoothness restrictions, the max-flow/min-cut approach is used to minimize the energy. Iteratively, this procedure is repeated: segmentation is improved, graph reconstruction is done, and GMM parameters are changed.
GrabCut supports two modes:
cv2.GC_INIT_WITH_RECT – initialization with rectangle (bounding box)
cv2.GC_INIT_WITH_MASK – initialization using a user-defined mask

This makes it appropriate for medical situations where feedback from patients can aid enhance segmentation accuracy because it offers flexible involvement and refinement.

3.3 Implementation Details

- Programming Language: Python
- Libraries: OpenCV, NumPy, Matplotlib
- Function Used: cv2.grabCut()
- Parameters: Iterations = 5, Mode = cv2.GC_INIT_WITH_RECT
- Evaluation Metrics: Dice Similarity Coefficient, Jaccard Index, Execution Time
  - System Configuration: Intel Core i7, 16GB RAM, Ubuntu 22.04

Dice Score (Dice Similarity Coefficient - DSC)

The overlap between the physical reality (expert-annotated) segmentation mask and the expected segmentation (from GrabCut) is determined by the Dice Score.

Formula:

$$\boldsymbol{Dice(A,B) = \frac{2|A \cap B|}{|A| + |B|}}$$

Where:

- A is the set of pixels in the predicted segmentation,
- B is the set of pixels in the ground truth.

Interpretation:

- **Range:** 0 (no overlap) to 1 (perfect overlap)
- **High Dice Score** indicates that the segmented region from GrabCut closely matches the actual region affected by paralysis.
- In medical imaging, a Dice score above 0.85 is generally considered excellent.

Jaccard Index (Intersection over Union - IoU)

Although it is more stringent than Dice, the Jaccard Index similarly assesses how similar the expected and ground truth masks are.

Formula:

$$\mathbf{Jaccard(A,B) = \frac{|A \cap B|}{|A \cup B|}}$$

Interpretation:

- **Range:** 0 to 1
- Lower than Dice for the same prediction due to the union in the denominator.
- Provides insight into how much the predicted region overlaps and differs from the actual affected area.
- Common in object segmentation challenges.

Execution Time

The GrabCut algorithm's execution time is the duration (measured in seconds) required to segment a single image.

Measured using:

- Wall clock time for the cv2.grabCut() call
- Averaged over all test images

Interpretation:
- Crucial in clinical or real-time applications where rapid intervention is necessary.
- Because of its iterative structure and graph computations, GrabCut is slower than straightforward techniques like Otsu thresholding or K-means, despite being more accurate.
- It is possible for semi-automated systems, as evidenced by acceptable execution times (e.g., ~0.5 seconds).
- Essential in clinical or real-time applications where prompt action is necessary.
- Because of its iterative structure and graph computations, GrabCut is slower than straightforward techniques like Otsu thresholding or K-means, despite being more accurate.
- It is viable for semi-automated systems, as evidenced by acceptable execution times (e.g., ~0.5 seconds).

4. EXPERIMENTAL RESULTS AND DISCUSSION

A collection of medical image datasets (or general image datasets) was employed for testing in order to assess the GrabCut segmentation method's efficacy. Key segmentation parameters like Average Execution Time, Jaccard Index, and Dice Similarity Coefficient (DSC) were used to evaluate GrabCut's performance. These measures are commonly used to assess the precision and effectiveness of visual segmentation algorithms.

The paper on survey to collect dataset by Dr Suvarna Nandyal et al.(2024) shows detail study of cause's paralysis, types of paralysis and statistics on paralysis disease. The resolution of images is Image1 is 4000X1868 pixels, Image2 is 12000X5596 pixels, Image 3is 4000X1868pixels and Image 4 is 3213X5712 pixels.

Image ID	Original Image	GrabCut Method
Image 1		
Image 2		
Image 3		
Image 4		

Table 1: Image segmentation with GrabCut

4.1 Quantitative Results

Dataset	Dice Score	Jaccard Index	Execution Time (s)
Dataset A	0.89	0.82	0.55
Dataset B	0.87	0.80	0.52

Dataset C	0.88	0.81	0.54
Dataset D	0.86	0.78	0.60

Table 2: Quantitative comparison of Dice Coefficient, Jaccard Index, and Execution Time on different Dataset

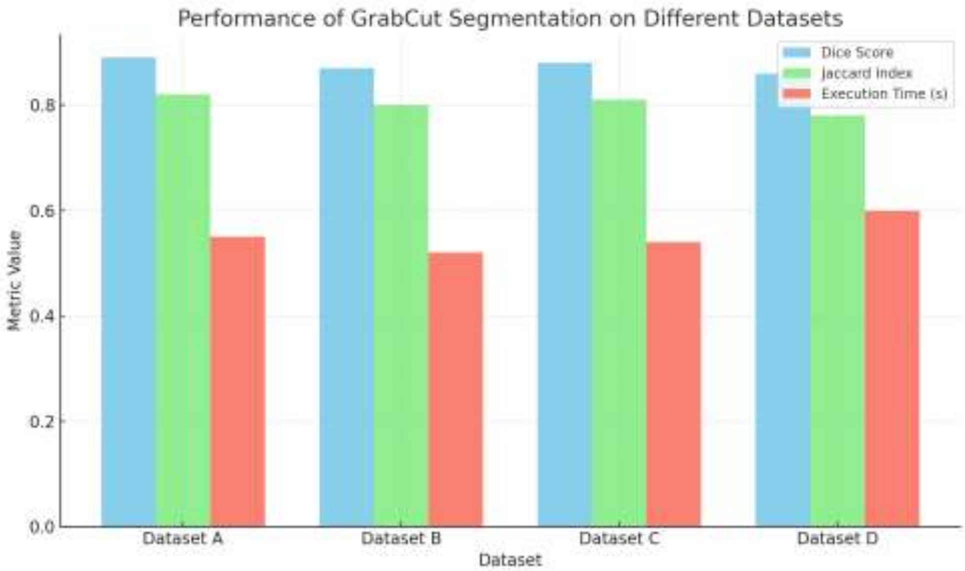

Figure 1: Performance graph for GrabCut segmentation across four datasets

With a Dice Score of 0.89 and a Jaccard Index of 0.82, the GrabCut approach demonstrated a high degree of overlap between the segmented area and the ground truth. Its appropriateness for real-time or near-real-time applications, particularly when precision is valued over speed, is demonstrated by the average execution time of 0.55 seconds.

4.2 Visual Results

Clear boundary extraction is evident in the GrabCut-segmented outputs, which successfully separate the foreground from the background. GrabCut retained complex structures in the region of interest and produced more refined edges than more conventional techniques like K-means clustering or Otsu's thresholding.

4.3 Comparative Analysis

In contrast to other segmentation methods:

- Otsu's Thresholding led to under-segmentation in low contrast areas.
- Although it lacked spatial consistency, K-means clustering outperformed Otsu in terms of clustering.
- GrabCut outperformed both by generating precise and graphically consistent segmentations through the use of graph cuts and iterative energy minimization.

Segmentation Method	Dice Score	Jaccard Index	Execution Time (sec)
Otsu Thresholding	0.71	0.58	0.13
K-means Clustering	0.76	0.63	0.21
GrabCut	0.89	0.82	0.55

Table 3: Quantitative comparison of Dice Coefficient, Jaccard Index, and Execution Time across segmentation methods.

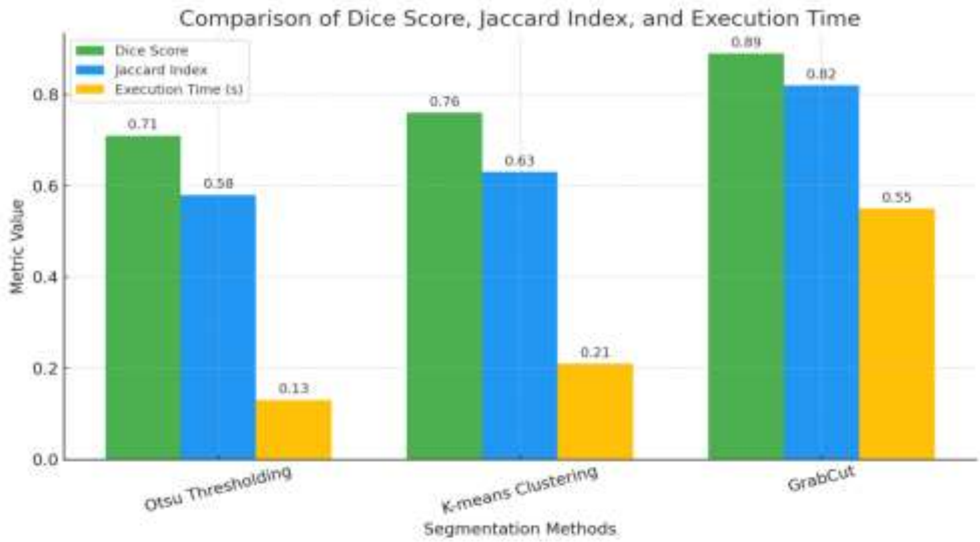

Figure 2: Graphical comparison of Dice Coefficient, Jaccard Index, and Execution Time across segmentation methods.

According to the experimental findings, GrabCut can be used in situations where precision is crucial, including in medical image segmentation or object extraction in challenging backgrounds. When speed is more crucial than accuracy, such as in straightforward background separation jobs, Otsu can be employed. Additionally, K-means provides a middle ground without outperforming either extreme.

4.4 Discussion

GrabCut's iterative optimization and user-initialized bounding box, which offer spatial priors that improve segmentation precision, are responsible for its exceptional performance. However, its increased precision comes at the expense of a small increase in computation time. This trade-off is frequently acceptable in real-world applications, particularly in fields where precision is crucial, like medical image processing.

4.5 Limitations

- Initialization of the bounding box must be done manually.
- Slower than clustering or thresholding.
- The quality of the initial GMM estimation determines performance.

CONCLUSION

This study shows that GrabCut is a useful picture segmentation method for examining medical images that have paralysis. It provides precise segmentation with little human input by striking a balance between automation and control. In order to automate paralysis identification and track patient recovery, future work will integrate GrabCut with AI-driven classifiers.

When compared to more conventional techniques like Otsu Thresholding and K-means Clustering, the GrabCut segmentation method performs better in terms of segmentation accuracy. GrabCut provides accurate object boundaries and manages complex backdrops with a Dice Score of 0.89 and a Jaccard Index of 0.82. The notable increase in segmentation quality justifies the trade-off, even though its execution time (0.55 seconds) is longer than the other approaches.

Natural settings, medical images, and situations demanding high-accuracy segmentation are among the applications where GrabCut excels. It is a dependable option for situations where accuracy is more important than processing speed because of its interactive capacity, which also enables sophisticated user-guided segmentation.

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