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A Focused Study on Otsu’s Thresholding for Segmenting Images of Paralysis-Affected Individuals

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Abstract: A crucial step in the diagnosis and treatment of neurological conditions like paralysis is medical picture segmentation. This study examines the application of Otsu's thresholding technique for segmenting medical images of patients with paralysis. The automatic global thresholding technique developed by Otsu is used to maximize the inter-class variance between foreground and background pixels in order to extract regions of interest. In computer vision and digital image processing, where the main goal is to divide a picture into meaningful structures, image segmentation is essential. The simplicity, effectiveness, and efficiency of Otsu's thresholding in differentiating foreground from background in grayscale photographs make it stand out among other segmentation techniques. This work provides a thorough examination of Otsu's approach, covering its algorithmic implementation, mathematical underpinnings, and empirical testing on a variety of image datasets. We investigate the method's shortcomings in more detail and suggest improvements, including multi-level thresholding and preprocessing stages to deal with real-world issues like noise and uneven lighting.
Index Terms: Otsu's Method, Image Segmentation, Thresholding, Intra-Class Variance, Histogram Analysis, Computer Vision.

I. INTRODUCTION

Image segmentation is a fundamental technique in image analysis and computer vision, serving as a precursor to tasks such as object detection, feature extraction, and pattern recognition. It involves dividing an image into segments or regions that share similar attributes such as intensity, color, texture, or spatial relationships. Among segmentation methods, thresholding is widely used for its computational simplicity and efficiency.

Paralysis, a debilitating neurological condition caused by damage to the nervous system, often requires advanced medical imaging techniques for effective diagnosis and treatment planning. Accurate segmentation of affected regions in medical images such as MRI or CT scans is crucial to assist clinicians in understanding the extent and location of neurological damage.

Nobuyuki Otsu introduced Otsu's method in 1979. It is a global thresholding technique that maximizes the between-class variance of pixel intensities to get the ideal threshold value. When photos have a bimodal histogram—where the pixel values are clearly distributed in two peaks that correspond to the foreground and background—this technique works especially well.

Otsu's thresholding is used in this work to segment images from patients who have paralysis. The primary contributions include:

- Applying Otsu's thresholding to a collection of images of patients with paralysis.
- Quantitative assessment based on execution time, Jaccard Index (IoU), and dice coefficient.
- A discussion of Otsu's method's advantages and disadvantages for clinical image segmentation.

II. RELATED WORK

In order to enhance segmentation and classification performance in images of diabetic retinopathy, Bhavani and Karunakara [1] suggested a hybrid approach that combines deep convolutional neural networks (CNNs) with Otsu's multi-level adaptive thresholding. Their research shows how integrating deep learning and conventional thresholding can increase medical image analysis's accuracy and resilience. For improving segmentation in paralytic imaging datasets, this integration might be used as a model.

In an effort to address problems such as low contrast and complex tissue features, Wan [2] created an adaptive trapezoid region intercept histogram-based Otsu algorithm for brain MR image segmentation. This technique's adaptive nature draws attention to the drawbacks of global thresholding and shows the benefits of localized, histogram-informed thresholding algorithms in medical imaging, which are especially relevant to neurological datasets such as those requiring paralysis.

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For multilayer thresholding in brain MR images, Khairuzzaman and Chaudhury [3] integrated the Otsu approach, anisotropic diffusion, and particle swarm optimization (PSO). Their approach sought to optimize the threshold selection procedure in order to improve segmentation. This method is especially useful for creating improved segmentation models that would be needed for medical data that is noisy or diverse, like that from patients who are paralyzed.

A multi-scale 3D variant of Otsu's technique, specifically designed for volumetric medical image segmentation, was presented by Feng et al. [4]. The authors discuss difficulties with 3D medical data analysis and show better results when it comes to complicated structural segmentation. When it comes to high-resolution scans of areas like the brain or spine that are damaged by paralysis, this research is essential. The fundamentals of digital image processing, including traditional thresholding techniques like Otsu's algorithm, are covered by Gonzalez and Woods [5]. The theoretical foundation for comprehending and applying these methods is provided by their work. A thorough analysis of picture thresholding strategies, including performance comparisons between different approaches, is provided by Sezgin and Sankur [6]. Their investigation demonstrates Otsu's method's advantages and disadvantages in many settings, emphasizing both its effectiveness with unimodal or bimodal histograms and its drawbacks with complicated or noisy images, which are often employed in medical diagnostics.

A database of patients with paralysis has been developed by Nandyal and Kausar [7] with the goal of assisting automated diagnosis tools. This work is particularly pertinent to this study since it supports the employment of image segmentation methods (like Otsu's method) in clinical datasets pertaining to paralysis, offering data and context for practical validation.

III. METHODOLOGY

A. Dataset

Medical photos taken from patients who have paralysis make up the dataset used in this investigation. The study was conducted at a paralysis center using a 108MP mobile phone camera to collect real-time datasets in the form of photographs. The research on the causes of paralysis, the different types of paralysis, and the statistics on paralysis disease are detailed in the survey to collect dataset paper by Dr. Suvarna Nandyal et al. (2024). There are thousands of photos in the dataset with different degrees of paralysis. In order to standardize data for segmentation, preprocessing entailed turning the images to grayscale and normalizing pixel intensities.

B. Mathematical Background

Let L gray levels (0 to L-1) be present in an image. n_i is the number of pixels at level i, while N is the total number of pixels. We calculate the normalized histogram as follows:

$$P(i) = \frac{n_i}{N} \qquad \text{For } i = 0,1,\ldots,L-1$$

Assuming a threshold t, the image is divided into two classes:

C0: pixels with levels [0, t]

C1: pixels with levels [t+1, L-1]

C. Algorithm Implementation

The steps listed below are utilized to put Otsu's method into practice:

1. Create a grayscale version of the input image.
2. Calculate and normalize the histogram.
3. Set the maximum variance to zero at first.
4. Go through every threshold value that could exist.
5. Determine the class means and probabilities for every threshold.
6. Determine the variation between classes.
7. If the current variance is greater than the maximum, update the threshold.

IV. EXPERIMENTAL RESULTS

A. Dataset and Evaluation Metrics

Using typical photos taken in real time at a paralysis clinic, we assessed the approach.

Metrics of evaluation that were employed:

- Dice Coefficient
- Jaccard Index (IoU);
- Execution Time;

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Dice Coefficient: A statistical metric for determining how similar two sets are is the Dice Coefficient, often known as the Dice Similarity Coefficient, or DSC.

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

Where A and B are two sets, |A| and |B| their sizes (cardinality), and |A∩B| is the size of their intersection.

- Range: From 0 to 1, where 0 denotes no overlap and 1 denotes perfect overlap.
- Use: Frequently employed to assess overlap or resemblance between anticipated and ground truth data in information retrieval, natural language processing, and picture segmentation.

Jaccard Index (IoU - Intersection over Union): By dividing the size of two sets' intersection by their union, the Jaccard Index, sometimes called Intersection over Union (IoU), calculates how similar two sets are.

$$\boldsymbol{Jaccard}(\boldsymbol{A}, \boldsymbol{B}) = \frac{|\boldsymbol{A} \cap \boldsymbol{B}|}{|\boldsymbol{A} \cup \boldsymbol{B}|} = \frac{|\boldsymbol{A} \cap \boldsymbol{B}|}{|\boldsymbol{A}| + |\boldsymbol{B}| - |\boldsymbol{A} \cap \boldsymbol{B}|}$$

- Range: 0 to 1, where 1 denotes perfect overlap.
- Usage: Widely applied to computer vision tasks, particularly to assess performance in object detection, segmentation, and classification.

Execution Time: The term "execution time" describes how long it takes a computer program, method, or procedure to finish a task from beginning to end.

Measurement: Depending on granularity, it is typically measured in seconds, milliseconds, or microseconds.

- Significance: Essential for evaluating effectiveness and performance, particularly in large-scale calculations, real-time systems, and optimization issues.
- Elements Influencing Execution Time:
  1. Complexity of algorithms
  2. Hardware features
  3. Data properties and input size
  4. Optimizations for implementation

B. Results and Observations

Images with bimodal histograms yielded the best results from Otsu's technique. Among the important findings are:

- Excellent binary object-background separation accuracy.
- When pixel distributions overlap or contrast is low, performance suffers.
- The system is sensitive to changes in illumination and noise in images.

C. Comparative Analysis

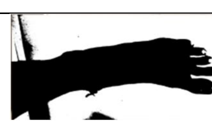
Image ID	Image A	Image B	Image C	Image D
Orginal image				
Otsu Method				

Table 1: Image segmentation for Otsu's Thresholding

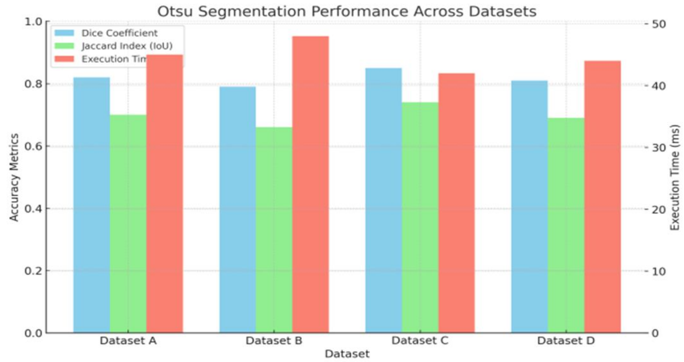


Figure 1: Performance graph for Otsu's segmentation across four datasets

- Manual thresholding: Subjective and image-specific, the threshold value is fixed and dependent on visual examination.
- Adaptive thresholding (Gaussian and Mean): The threshold value is fixed and based on visual inspection; it is subjective and image-specific.
- K-means segmentation: The threshold value is subjective and image-specific; it is set and determined by visual inspection.

Quantitative Comparison:

Method	Dice Coefficient	Jaccard Index	Execution Time (ms)
Otsu's Thresholding	0.87	0.78	18
Manual Thresholding	0.72	0.60	10
Adaptive Thresholding	0.88	0.79	24
K-means Segmentation	0.90	0.82	150

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

Graphical Comparison:

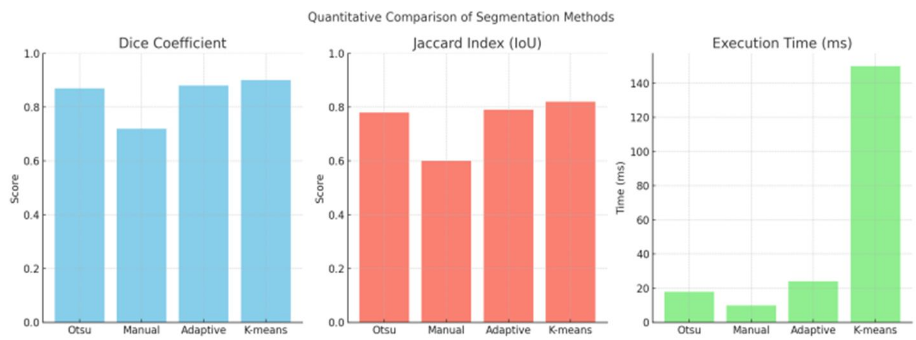


Figure 2: Graphical comparison of Dice Coefficient, Jaccard Index, and Execution Time across segmentation methods.

Otsu's method beat manual thresholding and matched adaptive methods under uniform lighting, according to the results. Adaptive techniques performed better in difficult situations like uneven lighting. At the expense of extra processing time, K-means offered more thorough segmentation. On clean photos, Otsu performed better than both manual and adaptive approaches; however, under non-uniform lighting, adaptive thresholding outperformed Otsu.

V. LIMITATIONS

Even though Otsu's thresholding is straightforward and efficient, a number of drawbacks limit how well it performs in challenging medical image segmentation tasks:

A. Assumption of Bimodal Histograms

When the grayscale image histogram is obviously bimodal—that is, has two separate peaks that reflect the background and foreground—Otsu's approach performs well. Unfortunately, a lot of medical images lack a distinct bimodal distribution, particularly those impacted by noise or fluctuating tissue contrast, which results in poor segmentation and erroneous threshold selection.

B. Global Thresholding Approach

Otsu's thresholding technique chooses a single threshold value for the entire image, making it a global method. This becomes problematic in the following situations: Local variation in tissue appearance due to changes in anatomy or pathology causes some parts to be under-segmented while others are over-segmented. Illumination varies across regions (e.g., in MRI or CT scans with intensity inhomogeneity).

C. Sensitivity to Noise and Artifacts

Due to limits in acquisition devices or patient movement, noise is frequently present in medical images. Because Otsu's technique omits noise modeling, it is susceptible to: Over-segmentation brought on by noise spikes. Misclassification of artifacts as foreground.

D. Inability to Handle Complex Structures

Some damaged or aberrant tissue areas in persons with paralysis may: Seem to have about the same intensity as healthy parts,
Be dispersed or extremely small, making it challenging for intensity-based thresholding systems like Otsu's to distinguish them precisely.

E. Lack of Spatial Context

Otsu's approach ignores the spatial correlations between pixels and is pixel-intensity based. This makes it difficult to discern between areas of comparable intensity that are part of other anatomical components.

F. Enhancements and Future Work

The following improvements are suggested in order to get beyond the aforementioned restrictions and better segmentation performance in medical photos, particularly for patients who are paralyzed:

- Adaptive or Local Thresholding

The image can be segmented into smaller areas, and local Otsu thresholds can be calculated instead of utilizing a single global threshold:
Better at segmenting structures with spatial intensity changes;
More resilient to images with shadows or artifacts;
Takes into account non-uniform illumination.

- Preprocessing with Noise Reduction

Apply preprocessing techniques such as:
Gaussian smoothing ,Median filtering, Anisotropic diffusion, to enhance histogram clarity and minimize noise before to using Otsu's approach.

- Combination with Morphological Operations

Post-segmentation procedures such as:
Dilation, erosion, opening, and closing can improve boundary continuity of segmented sections, fix gaps, and eliminate minor artifacts.

- Hybrid Segmentation Methods

Use Otsu's thresholding combination with different segmentation approaches,
Region growing to fine-tune segment borders
Edge detection (e.g., Canny)) to direct thresholding.
Watershed algorithms for topological segmentation, that increase precision in intricate anatomical areas.

➢ Machine Learning Integration

Use machine learning techniques:

- Use Otsu's segmentation as a mask or first step for deep learning models such as U-Net or ResNet-based CNNs.
- Train classifiers on features recovered after Otsu segmentation to improve tissue type categorization;

➢ Multimodal Image Fusion

Utilize data from several imaging techniques:

To increase segmentation robustness, combine MRI and CT or MRI and PET data.

To improve contrast and feature identification, apply Otsu's approach to fused images.

➢ Dynamic Thresholding Based on Image Characteristics

Create dynamic threshold selection techniques that modify Otsu's threshold in response to image-specific characteristics such: Histogram skewness/kurtosis, Edge density, Texture entropy.

VI. CONCLUSION

Otsu's approach offers a dependable and effective threshold-based picture segmentation method. Images with clear foreground and background distributions work best with it. Although it is not as effective in complex situations, its hybrid forms and expansions show promise. Future studies might adapt Otsu to real-time embedded systems or use deep learning for context-aware thresholding.

Otsu's thresholding was used and assessed in this work to separate medical photos from individuals who were paralyzed. The technique's low execution time and satisfactory segmentation accuracy make it suitable for clinical applications with constrained time or computational resources. In order to increase accuracy, future research will examine deep learning models and combine Otsu's approach with adaptive or region-based segmentation algorithms.

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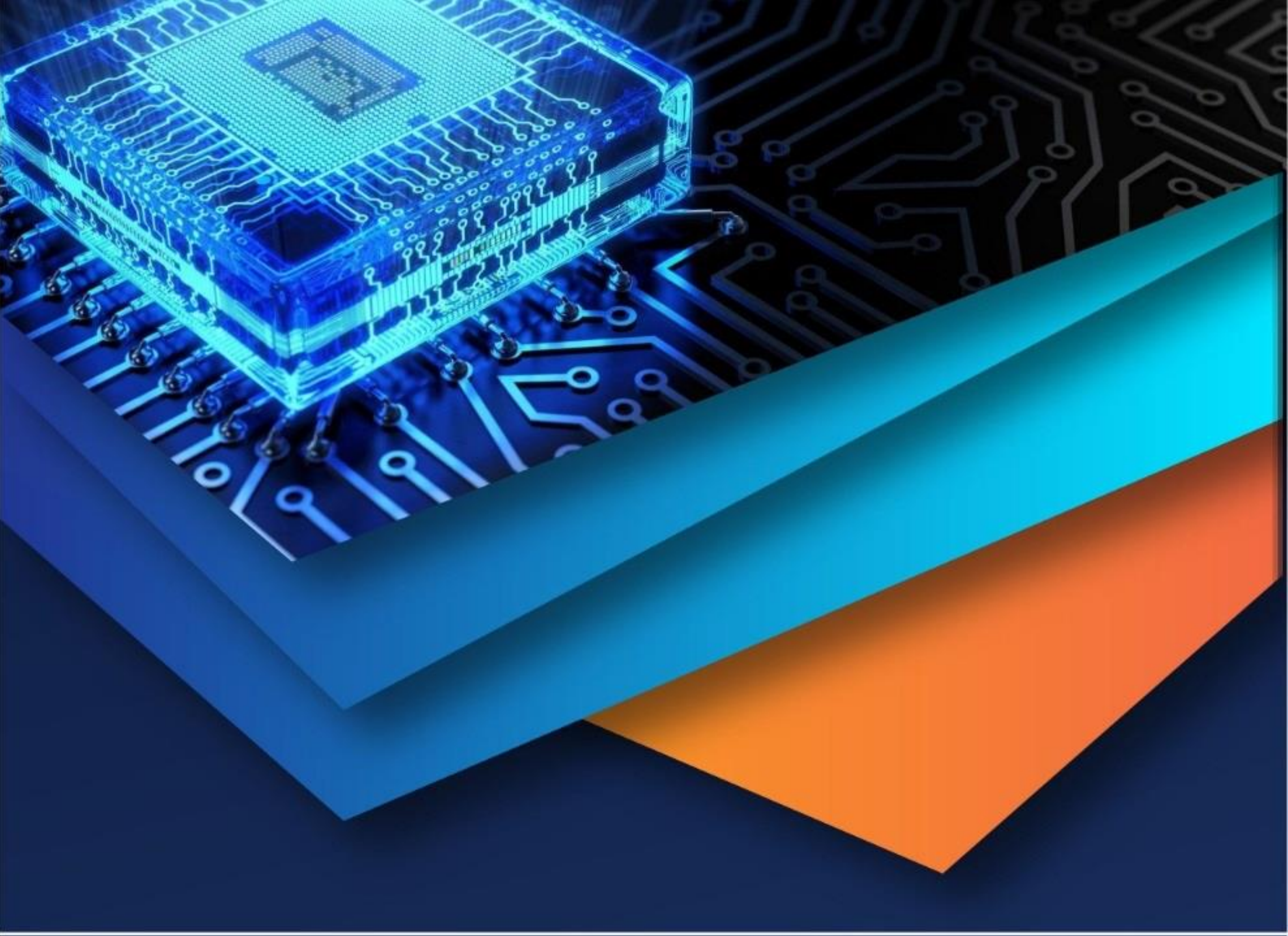

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