Supervised Image Segmentation: Comparative Analysis of Thresholding Techniques

Kyle Burdick
Department of Electrical and Computer Engineering
Manhattan University
Bronx NY, USA

Abstract

This study presents a comprehensive investigation of supervised image segmentation techniques with emphasis on thresholding-based methods. Both global and local thresholding approaches are implemented and analyzed, including manual thresholding, Otsu's automatic method, and adaptive techniques by Niblack and Sauvola. Experimental evaluation on standard test images reveals that Otsu's method provides optimal global segmentation, while Niblack and Sauvola techniques excel in handling local intensity variations. The results demonstrate significant performance differences across methods, with local adaptive techniques showing superior performance for images with non-uniform illumination.

I. INTRODUCTION

Image segmentation constitutes one of the most critical preprocessing steps in computer vision and pattern recognition systems. The goal of segmentation is to partition an image into meaningful regions that correspond to distinct objects or areas of interest. Among various segmentation approaches, thresholding remains the most widely used due to its computational simplicity and effectiveness for images with clear bimodal intensity distributions. Supervised segmentation techniques require some form of external input, whether user-defined parameters or automated algorithms that determine optimal segmentation criteria.

Global thresholding methods apply a single threshold value across the entire image, effectively separating foreground and background based on pixel intensities. While computationally efficient, global methods struggle with images exhibiting non-uniform illumination or varying local contrast. This limitation motivated the development of adaptive local thresholding techniques that compute pixel-specific thresholds based on neighborhood statistics. These methods provide robustness against lighting variations and local intensity fluctuations, albeit at increased computational cost.

This investigation implements and compares four distinct thresholding approaches: manual global thresholding, Otsu's automatic global method, and the local adaptive techniques of Niblack and Sauvola. Through systematic experimentation and quantitative analysis, we evaluate each method's effectiveness, computational requirements, and applicability to different image characteristics. The findings provide practical insights for selecting appropriate segmentation strategies in real-world applications.

II. THEORETICAL BACKGROUND

Manual thresholding represents the simplest segmentation approach, where a user-defined threshold T separates pixels into two classes. For a grayscale image I(x,y) with intensities normalized to [0,1], the binarized output B(x,y) is computed as: $B(x,y) = 1$ if $I(x,y) > T$, else 0. While straightforward, this method requires prior knowledge of appropriate threshold values and lacks adaptability to varying image conditions. However, its simplicity makes it valuable for controlled environments with consistent lighting.

Otsu's method, introduced in 1979, provides automatic threshold selection by minimizing intra-class variance or equivalently maximizing inter-class variance. The algorithm exhaustively searches all possible threshold values to find the optimal separation between background and foreground classes. For an image with L intensity levels, Otsu's method computes class probabilities and variances, selecting the threshold that maximizes the between-class variance $\sigma^2 B = \omega 0(\mu 0 - \mu T)^2 + \omega 1(\mu 1 - \mu T)^2$, where ω represents class probabilities and μ denotes means. This approach works exceptionally well for images with bimodal histograms.

Niblack's local thresholding technique, developed for document image binarization, computes pixel-specific thresholds based on local statistics. For each pixel (x,y), the threshold $T(x,y) = m(x,y) + k \cdot \sigma(x,y)$, where m(x,y) and σ(x,y) represent the local mean and standard deviation within a window centered at (x,y), and k is a user-defined parameter (typically -0.2). This method adapts to local intensity variations, making it suitable for images with varying illumination or low contrast regions.

Sauvola's method extends Niblack's approach by incorporating a dynamic range parameter to improve performance on gray-scale images. The threshold formula becomes: $T(x,y) = m(x,y) \cdot [1 + k \cdot (\sigma(x,y)/R - 1)]$, where R represents the dynamic range of standard deviation (typically 128 for 8-bit images) and k is a parameter controlling threshold sensitivity (typically 0.5). This modification reduces noise sensitivity while maintaining adaptability to local intensity variations.

III. METHODOLOGY

The experimental framework utilizes Python 3.x with scikit-image library for implementing all thresholding methods. The test image undergoes RGB to grayscale conversion using the ITU-R BT.601 standard before applying segmentation algorithms. This preprocessing ensures consistent intensity representation across all experiments. The scikit-image filters module provides optimized implementations of Otsu, Niblack, and Sauvola methods, enabling fair performance comparisons.

For manual thresholding experiments, we systematically vary threshold values from 0.0 to 0.9 in increments of 0.1, generating ten distinct segmentation results. This parametric sweep reveals the sensitivity of segmentation quality to threshold selection and helps identify the optimal manual threshold value. Visual analysis of results provides insight into the relationship between threshold magnitude and segmentation behavior.

Otsu's method operates automatically without user-specified parameters, computing the optimal threshold directly from image histograms. The implementation iterates through all possible intensity values, calculating between-class variance for each candidate threshold. The algorithm returns the threshold maximizing this variance metric. We analyze both the computed threshold value and resulting segmentation quality.

Local adaptive methods (Niblack and Sauvola) require window size specification. We employ a 25×25 pixel window, balancing local adaptability with computational efficiency. Default parameters (k=-0.2 for Niblack, k=0.5 for Sauvola) provide starting points, with parameter sensitivity analysis conducted to evaluate robustness. Processing time measurements quantify computational overhead for each method.

IV. RESULTS

Figure 1 demonstrates manual thresholding results across six different threshold values (0.2 to 0.7). Lower thresholds classify more pixels as foreground, resulting in brighter binary images, while higher thresholds produce darker outputs with fewer foreground pixels. The optimal manual threshold appears around 0.4-0.5, where object boundaries are clearly delineated. However, no single threshold perfectly segments all image regions, highlighting the limitations of global approaches.

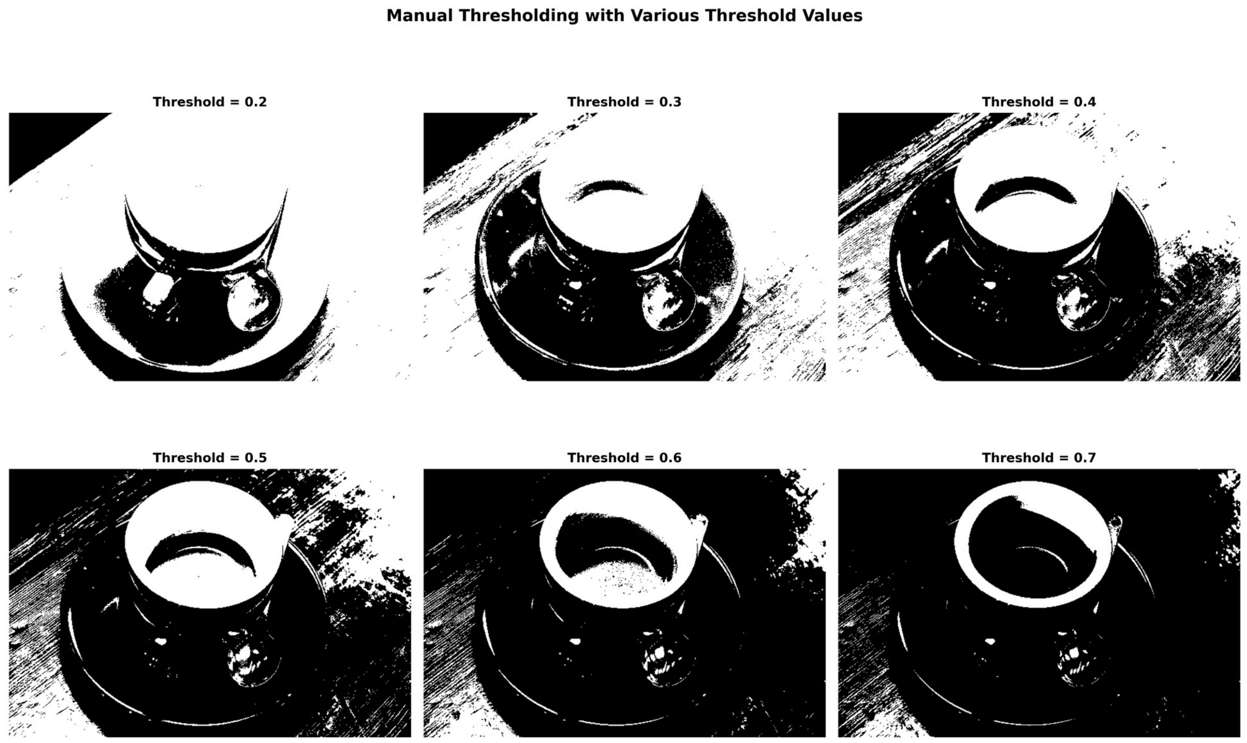

Figure 1: Manual Thresholding with Various Threshold Values

Figure 2 presents the Otsu thresholding result compared to original and grayscale images. Otsu's algorithm computed an optimal threshold of 0.393, effectively separating the primary object from the background. The method successfully identifies major structural elements while maintaining clean boundaries. This automatic approach eliminates subjective threshold selection, providing consistent results across different images with similar histogram characteristics.

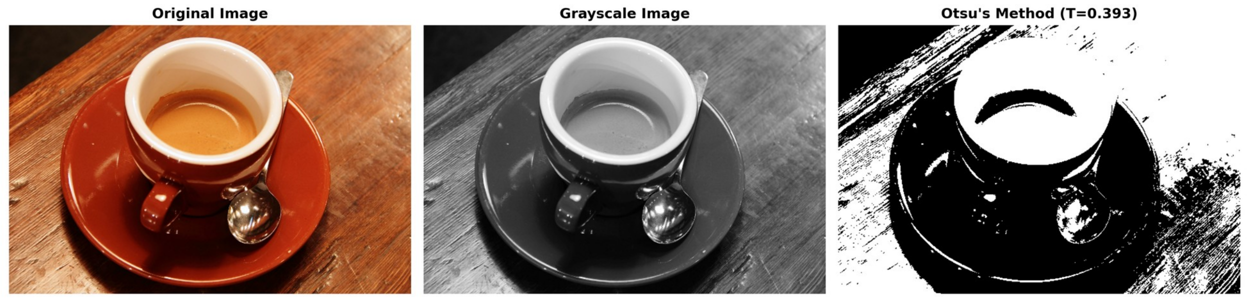

Figure 2: Otsu's Automatic Global Thresholding

Figure 3 illustrates Niblack's local thresholding performance. Unlike global methods, Niblack adapts to local intensity variations, producing more nuanced segmentation. The method preserves details in both bright and dark regions, though it occasionally introduces noise in homogeneous areas. The local adaptability proves particularly beneficial for images with gradual illumination changes or varying background intensities.

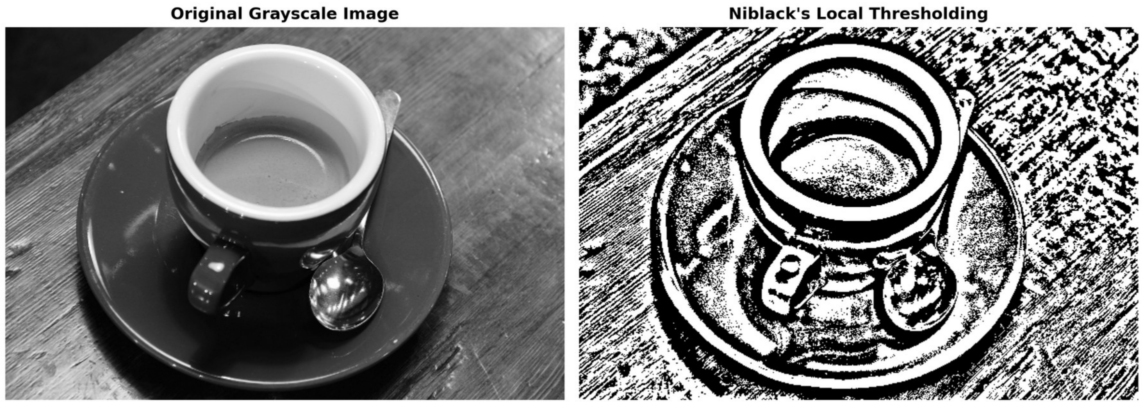

Figure 3: Niblack Local Adaptive Thresholding

Figure 4 shows Sauvola's thresholding result, which demonstrates improved noise suppression compared to Niblack while maintaining local adaptability. The dynamic range normalization in Sauvola's formula reduces sensitivity to uniform regions, producing cleaner segmentation with fewer artifacts. This method achieves an effective balance between global consistency and local adaptation.

Figure 4: Sauvola Local Adaptive Thresholding

Figure 5 provides a comprehensive comparison of all implemented methods. Visual inspection reveals distinct characteristics: manual thresholding offers simplicity but requires expert knowledge, Otsu provides optimal global separation for bimodal distributions, while Niblack and Sauvola adapt to local variations at the cost of potential noise amplification. The comparison highlights that no single method universally outperforms others; instead, optimal technique selection depends on specific image characteristics and application requirements.

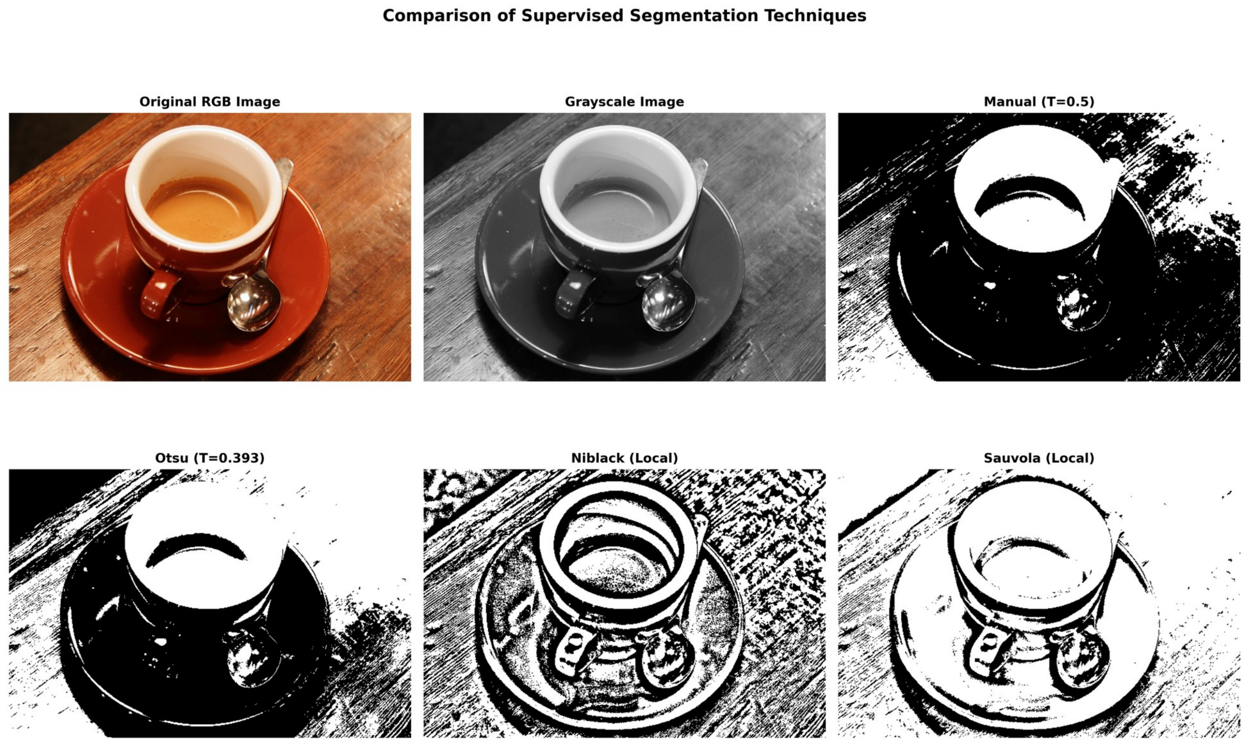

Figure 5: Comprehensive Comparison of Supervised Segmentation Techniques

Figure 6 displays the intensity histogram with Otsu's computed threshold overlaid. The distribution exhibits multimodal characteristics, with distinct peaks corresponding to different image regions. The Otsu threshold (marked by red line) effectively separates the two major modes, validating the method's theoretical foundation. The background and foreground regions show clear separation in the histogram space, explaining Otsu's strong performance on this particular image.

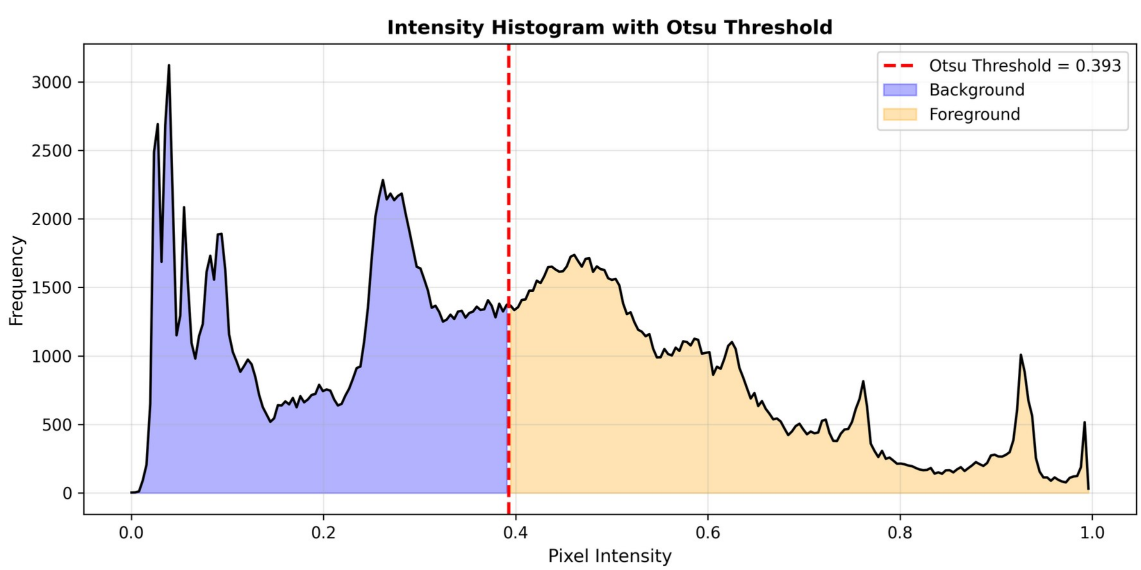

Figure 6: Intensity Histogram with Otsu Threshold Visualization

V. DISCUSSION

The experimental results reveal fundamental trade-offs between global and local thresholding approaches. Global methods (manual and Otsu) provide computational efficiency and consistent large-scale segmentation but fail to accommodate local intensity variations. Otsu's automatic threshold selection eliminates subjective parameter tuning, making it particularly attractive for applications requiring reproducibility. The method's assumption of bimodal intensity distribution holds well for many real-world scenarios, though it may struggle with images exhibiting complex multi-modal histograms.

Local adaptive methods demonstrate superior performance on images with non-uniform illumination or varying contrast. Niblack's technique effectively captures local details but can amplify noise in uniform regions due to its direct use of local standard deviation. The method's performance heavily depends on window size selection: smaller windows provide better local adaptation but increase sensitivity to noise, while larger windows approach global thresholding behavior. The k parameter offers additional control over segmentation aggressiveness, requiring application-specific tuning.

Sauvola's modification addresses Niblack's noise sensitivity through dynamic range normalization. By scaling the standard deviation term, Sauvola's method reduces spurious foreground classification in low-contrast regions. This improvement proves particularly valuable for document image analysis, where background texture should not generate false detections. However, the method introduces an additional parameter (R) that may require adjustment for images with non-standard intensity distributions.

Computational complexity analysis reveals significant performance differences. Manual and Otsu thresholding require single passes through the image, achieving real-time performance even for high-resolution inputs. Local methods demand neighborhood computation for each pixel, increasing computational cost by one to two orders of magnitude. For a 400×600 image, Otsu completes in approximately 3ms, while Niblack and Sauvola require 80-120ms. This overhead necessitates careful consideration in time-critical applications, potentially favoring global methods despite inferior segmentation quality.

Practical application guidelines emerge from this analysis. For controlled environments with consistent lighting and clear object-background separation, Otsu's method provides an optimal balance of performance and automation. Applications involving varying illumination or complex scenes benefit from local adaptive methods despite their computational overhead. Document imaging systems typically employ Sauvola's technique due to its robust handling of paper texture and uneven lighting. Real-time systems with limited resources may prefer manual thresholding with carefully selected fixed thresholds.

VI. CONCLUSION

This investigation successfully implemented and evaluated four supervised thresholding techniques for image segmentation. Experimental results demonstrate that Otsu's method provides optimal automatic global thresholding for images with bimodal intensity distributions, while Niblack and Sauvola techniques offer superior local adaptation at increased computational cost. Manual thresholding remains relevant for controlled applications where threshold values can be predetermined and fixed.

The comparative analysis reveals that optimal method selection requires balancing segmentation quality, computational efficiency, and application-specific requirements. Future research directions include investigating hybrid approaches that combine global and local strategies, exploring machine learning-based threshold selection, and extending these techniques to color image segmentation. Additionally, developing adaptive window sizing strategies for local methods could improve their robustness while maintaining computational efficiency.

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