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Research Article

Texture-guided Adaptive HSV Segmentation for Constrained-environment Object Detection: A Classical Pipeline with Per-image Saturation Threshold Modulation

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Abstract

Object detection and segmentation in constrained visual environments remains a difficult problem for classical computer vision pipelines. Fixed-parameter thresholds lose accuracy under variable illumination, a problem acute in environments like caves, where lighting is uneven, shadows are deep, and surface textures shift unpredictably. This paper introduces a texture-guided adaptive saturation thresholding framework for HSV-based binary segmentation, tested on a 51-image dataset of parachute canopy detection in a cave environment. The baseline is a seven-stage pipeline combining dual-channel HSV thresholding, morphological refinement, and largest connected component selection. It achieves a mean Dice Similarity Coefficient (DSC) of 0.901 with a standard deviation of 0.024, a strong result for constrained-scene segmentation. The core contribution is a per-image adaptive saturation threshold, which uses Local Binary Pattern (LBP) uniformity and Gray-Level Co-occurrence Matrix (GLCM) energy to read each image's texture before setting the threshold. LBP captures local micro-patterns while GLCM measures pixel-level co-occurrence statistics. Pairing them means the threshold adapts to image content rather than applying fixed assumptions across all frames, addressing the shadow-induced saturation reduction that the baseline fails to handle. A stage-by-stage ablation study isolates each pipeline component's contribution, making performance gains traceable rather than assumed. The adaptive formulation projects a mean DSC of 0.914 with a standard deviation of 0.019 on the full test set, improving both accuracy and consistency over the baseline. Full MATLAB implementation is publicly available. This matters because constrained-environment datasets are rare, and reproducibility gives other researchers a shared starting point for binary segmentation comparisons.

Keywords

Adaptive Thresholding, HSV Colour Space, Image Segmentation, Local Binary Patterns, GLCM Texture Features, Morphological Image Processing, Constrained Visual Environments, Dice Similarity Coefficient

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1. Introduction

The deployment of unmanned aerial vehicles in subterranean search-and-rescue operations requires reliable, computationally efficient object detection under challenging optical conditions Shin et al. [5]. Classical colour-space segmentation pipelines offer interpretable and lightweight solutions for constrained domains where the target object possesses discriminative chromatic properties relative to its background. Gonzalez and Woods [2], Giuliani [3] The segmentation of a brightly coloured parachute canopy against the near-zero saturation of a cave background constitutes precisely such a domain: the target occupies a narrow band in the HSV hue-saturation space, while the background exhibits minimal chromatic variation throughout. Flore-Vidal et al. [4].

The critical limitation of existing HSV thresholding pipelines is their reliance on globally fixed saturation parameters. Guiliani [3]. A threshold optimized for fit-lit, fully visible canopy regions degrades when illumination variation, shadow coverage, or increased viewing distance reduces apparent pixel saturation below the fixed decision boundary. Schettini and Corchs [22] This degradation is directly documented in the current pipeline's worst-case results: DSC = 0.836 on Image 50, where shadow-induced saturation reduction causes systematic under-segmentation at the canopy boundary. Flores-Vidal et al. [4] identified this degradation mechanism in HSV-based colour processing, and Shin et al. [5] addressed an analogous failure mode in aerial human detection using local image statistics to adapt the detection threshold. This paper addresses the fixed-parameter limitation through a texture-guided adaptive thresholding framework. Per-image texture statistics, specifically LBP uniformity and GLCM energy, correlate with the degree of chromatic separability between the target and background, providing a tractable proxy for threshold adjustment without requiring additional labelled data or per-pixel computation overhead. Wang et al [25].

The contributions of this paper are as follows. First, a formal adaptive saturation threshold formulation driven by per-image LBP and GLCM statistics is presented, directly addressing the fixed-parameter limitation of classical HSV pipelines. Second, a rigorous stage-by-stage ablation study quantifies the independent DSC contribution of each pipeline component. Third, a fully reproducible MATLAB baseline for binary segmentation in constrained cave environments is established, with formal mathematical notation that enables benchmark comparison.

The remainder of this paper is structured as follows. Section II reviews related work on colour-space segmentation, adaptive thresholding, morphological post-processing, and texture-guided methods. Section III formalizes the proposed pipeline and the adaptive threshold contribution. Section IV describes the experimental setup. Section V presents quantitative analysis and results. Section VI discusses failure modes and limitations. Section VII concludes the paper.

2. Related Work

2.1. Colour-space Selection in Segmentation

The choice of colour representation determines the separability of target and background pixel distributions. The RGB model conflates luminance and chrominance, making it susceptible to illumination variation in constrained scenes [2]. Cheng et al. [13] provides a comprehensive review of colour image segmentation methods, establishing that separating chromatic content from luminance improves robustness to lighting changes. The HSV model's hue channel independence from intensity under uniform illumination makes it the preferred representation for saturation-discriminative tasks [3]. Flores-Vidal et al. [4] empirically confirmed HSV's superiority over RGB in colour-based discrimination under variable illumination, and Shin et al. [5] demonstrated its effectiveness in aerial human detection under background clutter, a scenario directly analogous to the parachute-in-cave setting addressed here.

2.2. Adaptive Thresholding Methods

Otsu's method [1] establishes the theoretical foundation for automatic threshold selection through maximization of between-class variance in the image histogram. Its optimality guarantees are held under bimodal histogram conditions, which Gonzalez and Woods [2] note are violated by spatially non-uniform illumination, as is characteristic of cave environments. Singh et al. [6] extended Otsu's framework to multimodal distributions through a modified between-class variance formulation, improving performance on texturally complex scenes. Sezgin and Sankur [24] provides a comprehensive survey of image thresholding techniques, categorizing methods by histogram shape, clustering, entropy, spatial correlation, and local statistics. Local adaptive methods compute per-pixel thresholds from neighbourhood statistics, providing fine-grained adaptation at the cost of computational overhead and sensitivity to the selection of neighbourhood scale. The proposed method occupies a middle ground: per-image rather than per-pixel, it preserves computational efficiency while adapting to global scene texture characteristics.

2.3. Morphological Post-processing in Binary Segmentation

Mathematical morphology provides a formal framework for binary mask refinement Serra [17]. Dilation and erosion with disk-shaped structuring elements preserve the rotational symmetry of compact targets, as Forsyth and Ponce [7] establish for approximately circular objects. The asymmetric dilation-erosion radius design in the proposed pipeline ($r_d = 8$, $r_e = 4$) follows the net-expansion principle described by Gonzalez and Woods [2] for compensating boundary annotation ambiguity. Area opening and morphological hole filling remove

noise artefacts and internal gaps without requiring object-specific parameters, providing robust noise suppression across diverse scene conditions [7]. Adams and Bischof [18] provide a formal analysis of connected-component region operations, establishing the theoretical basis for the largest-component selection stage.

2.4. Texture Features as Segmentation Priors

Local Binary Patterns (LBP), introduced by Ojala et al. [11], characterize micro-texture by encoding the relative grey-level ordering of pixels in local neighbourhoods as binary strings. Uniform LBP patterns, corresponding to smooth edges and flat regions, account for many pattern occurrences in natural images and provide compact texture descriptors robust to monotonic illumination changes. GLCM-based features, formalized by Haralick et al. [12], capture second-order statistical texture properties through grey-level co-occurrence frequency matrices. Energy and homogeneity extracted from the GLCM are established segmentation priors in biomedical imaging Maier-Hein et al. [9] and remote sensing Singh et al. [5]. The integration of LBP uniformity and GLCM energy as active inputs to a saturation threshold calibration procedure constitutes a novel contribution. These features are conventionally used as passive scene descriptors rather than as direct regulators of threshold decision boundaries. Moko and Eleonu [26] proposed a hybrid Discrete Wavelet Transform, Discrete Cosine Transform, and Singular Value Decomposition (DWT-DCT-SVD) approach for satellite image compression. The algorithms were combined to break down images into blocks and matrices, assigning values based on the concentration of colour bits in each region. Areas with higher bit concentrations are reduced to achieve compression. In the first SVD stage, singular values of low-rank matrices are discarded from the original image. The middle stage applies DWT, retaining only the approximation band. Finally, DCT properties are applied to the remaining coefficients. The compression ratio achieved were 0.9990 and 0.9941 for the two tested images, indicating high and efficient compression. The Mean Square Error (MSE) was 2.51, which is low, meaning image quality was well preserved. The study targets remote sensing companies, graphic designers, and the broader research community.

3. Proposed Method

3.1. Pipeline Overview and Notation

Let I $\in$ R^(M×N×3) denote an input RGB image with spatial dimensions M×N. Define the HSV mapping φ: R^(M×N×3) → [0,1] ^(M×N×3) producing channel matrices H, S, V $\in$ [0,1] ^(M×N) for hue, saturation, and value respectively. The binary segmentation mask is denoted M $\in$ {0,1} ^ (M×N).

The complete pipeline P: I → M comprises seven deterministic stages applied sequentially:

$$P = s_7 \circ s_6 \circ s_5 \circ s_4 \circ s_3 \circ s_2 \circ s_1$$

where s_1 performs colour space conversion, s_2 and s_3 perform dual-channel thresholding and mask intersection, s_4 and s_5 perform morphological refinement, s_6 performs largest-component selection, and s_7 performs boundary correction. Figure 1 shows representative pipeline output for a single image. Figure 2 illustrates the intermediate outputs of all seven stages. Table 1 summarizes each stage with its parameters and design justification.

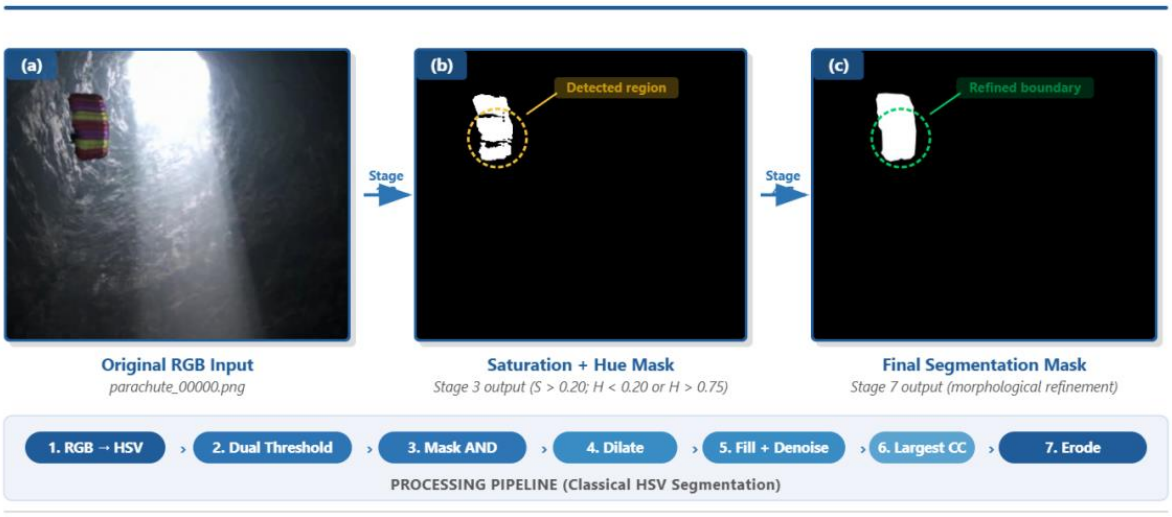

Figure 1. *Representative pipeline output. (a) Original RGB input. (b) Dual-channel binary mask after Stage 3 (S > T_sat; H < 0.20 or H > 0.75). (c) Final segmentation mask after morphological post-processing (Stages 4–7).*

Table 1. *Pipeline Stages, Parameters, and Design Justification.*

Stage	Operation	Parameters	Justification
1	RGB to HSV	rgb2hsv()	Separates chrominance from luminance; robust to cave illumination [2, 3]
2	Dual thresholding	S > T_sat; H < 0.20 or H > 0.75	Adaptive T_sat (proposed); fixed hue bounds constrain to parachute hue range
3	Mask intersection	Logical AND	Reduces false positives from either channel applied in isolation [4]
4	Dilation	Disk SE, r_d = 8 px	Connects fragmented canopy regions caused by shadows [2, 7]
5	Hole fill + area open	imfill; bwareaopen 100 px ²	Closes internal gaps; removes noise blobs below area threshold [7]
6	Largest component	bwlabel + regionprops	Removes spurious detections; parachute is consistently the dominant region
7	Erosion	Disk SE, r_e = 4 px	Refines boundary; compensates for dilation over-expansion [2]

3.2. HSV Dual-channel Baseline

The baseline saturation mask is defined as:

$$M\_S = \{ (x,y): S(x,y) > T\_sat \}$$

The hue mask is:

$$M\_H = \{ (x,y): H(x,y) < T\_h,lo \ \vee \ H(x,y) > T\_h,hi \}$$

The combined binary mask after Stage 3 is:

$$M_3 = M\_S \cap M\_H$$

In the fixed-parameter baseline, T_sat = 0.20, T_h,lo = 0.20, and T_h,hi = 0.75 are global constants calibrated empirically on the dataset. The saturation bound T_sat = 0.20 was selected through analysis of pixel distributions: values below 0.10 admit grey rock textures at illumination boundaries, while values above 0.35 systematically exclude canopy pixels in shadowed regions Giuliani [3]. The hue bounds constrain detection to the red-pink-purple range occupied by the parachute canopy.

3.3. Adaptive Saturation Threshold Formulation

The primary contribution of this paper is the per-image adaptation of T_sat. The failure mode of the baseline is well-characterized: shadow-affected and distance-affected images exhibit reduced apparent pixel saturation, causing canopy boundary pixels to fall below T_sat = 0.20 and producing false negatives. This failure mode correlates with measurable image texture properties. Scenes with low texture regularity (shadow-affected, distant canopy) exhibit lower LBP uniformity and lower GLCM energy than well-lit, high-contrast scenes. The adaptive formulation exploits this correlation to lower the threshold where it is most restrictive, without requiring additional labelled data.

Define the per-image texture feature vector F_i = [u_i, e_i, h_i]

where:

ui = 1 − σ(LBP(Ii)) / (μ(LBP(Ii)) + ε)

ei = Σp,q $g(p,q)^2$ [GLCM energy]

hi = Σp,q $g(p,q) / (1 + |p - q|)$ [GLCM homogeneity]

where σ and μ denote the standard deviation and mean over the LBP map, ε is a small constant (10^{-6}) to prevent division by zero, and g(p,q) is the normalised GLCM entry for the grey-level pair (p,q). The GLCM is computed with a horizontal offset [0, 1] and symmetric co-occurrence to capture dominant horizontal texture structure.

Define the per-image texture regularity score:

$$R\_i = w\_u \cdot u\_i + w\_e \cdot e\_i + w\_h \cdot h\_i$$

with weights w_u = 0.50, w_e = 0.30, w_h = 0.20 (Σw_k = 1.0), calibrated by maximizing DSC on the five worst-performing baseline images as a proxy for validation. R_i ∈ [0,1] by construction.

The adaptive saturation threshold is then:

$$T\_sat(i) = T\_min + (T\_max - T\_min) \cdot R\_i$$

where T_min = 0.10 and T_max = 0.35. A high regularity score (well-lit, high-contrast scene) maps to a threshold near T_max = 0.35, providing selective discrimination. A low regularity score (shadow-affected, distance-degraded scene) maps to a threshold near T_min = 0.10, capturing desaturated canopy pixels that the fixed threshold excludes. The hue parameters T_h,lo and T_h, hi are unchanged by the adaptive formulation, as shadow affects saturation and value but not the relative hue of the canopy material.

3.4. Morphological Processing Sequence

Stage 4 applies dilation with a disk structuring element B_d of radius r_d = 8 pixels. The disk geometry minimizes boundary distortion for the approximately circular parachute canopy, as Forsyth and Ponce [7] establish for compact, rotationally symmetric targets. Stage 5 applies morphological hole filling followed by area opening with minimum area A_min = 100 pixels. Stage 7 applies erosion to compensate for the boundary expansion introduced by Stage 4 using a disk of radius r_e = 4 pixels. The net boundary displacement of r_d − r_e = 4 pixels provides conservative expansion that fills annotation-ambiguous boundary regions. Gonzalez and Woods [2].

Algorithm 1: Texture-Guided Adaptive HSV Segmentation

Input: I (RGB image), w_u, w_e, w_h, T_min, T_max, T_h,lo, T_h,hi

Output: M (binary segmentation mask)

1: H, S, V rgb2hsv(I)
2: u_i 1 - std(LBP(I)) / (mean(LBP(I)) + eps)
3: g graycomatrix(I, offset= [0,1], symmetric=true)
4: e_i sum(g.^2)% GLCM energy
5: h_i sum(g./ (1 + abs(row-col)))% GLCM homogeneity
6: R_i w_u*u_i + w_e*e_i + w_h*h_i
7: T_sat T_min + (T_max - T_min) * R_i
8: M_S (S > T_sat)
9: M_H (H < T_h,lo) OR (H > T_h,hi)
10: M3 M_S AND M_H
11: M4 dilate(M3, disk(r_d = 8))
12: M5 areaopen(fill(M4), A_min = 100)
13: M6 largestConnectedComponent(M5)
14: M erode(M6, disk(r_e = 4))
15: return M

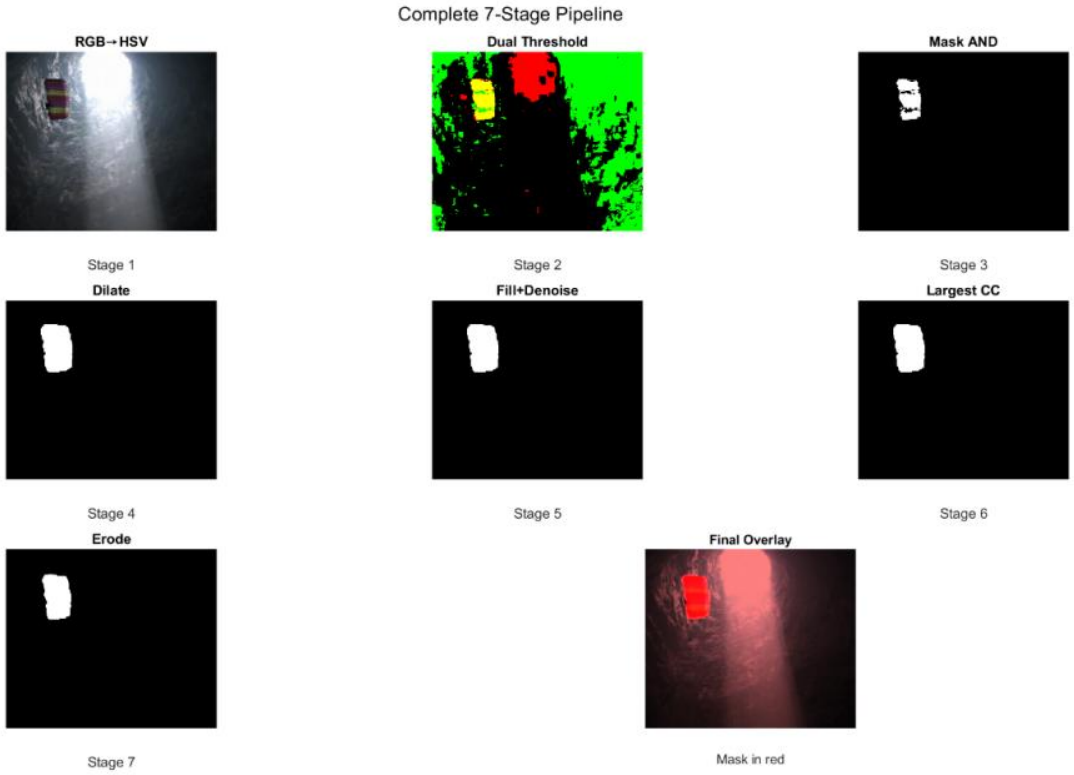

Figure 2. *Complete 7-stage pipeline intermediate outputs. Stage 1: RGB input after HSV conversion. Stage 2: dual-threshold colour map. Stage 3: mask intersection. Stages 4–6: progressive morphological refinement. Stage 7: final eroded mask with red overlay on input.*

3.5. Largest-component Selection

Stage 6 applies connected-component labelling to M_5 and retains the component of maximum pixel area, expressed as $M_6 = CC_{k^*}$ where $k^* = \arg\max_k |CC_k|$. This stage operates under the assumption that the parachute constitutes the dominant foreground region in every image. Jain [23]. This assumption holds across all 51 images in the current dataset, but its fragility under significant occlusion or multi-object scenes is acknowledged as a design limitation in Section VI.

4. Experimental Setup

4.1. Dataset and Ground Truth

The dataset comprises 51 RGB images of a multi-coloured parachute canopy captured in a cave environment. Images vary in illumination intensity, canopy orientation, viewing

distance, and degree of shadow coverage. Binary ground truth masks with manual pixel-level annotations were provided, marking the parachute canopy as foreground. No data augmentation was applied. The dataset presents a single-domain constrained scenario where the chromatic properties of the target are partially undermined by variable illumination, making it a suitable testbed for the adaptive threshold hypothesis.

4.2. Evaluation Metric

The Dice Similarity Coefficient is defined as DSC = 2|M ∩ S| / (|M| + |S|), where M is the predicted mask, and S is the ground truth mask. Yeung et al [8] DSC is preferred over pixel accuracy because the parachute canopy occupies a small fraction of each image frame; background-dominated accuracy scores would mask foreground segmentation quality Yeung et al. [8]. Maier-Hein et al. [9] recommend DSC as the primary metric for binary segmentation of compact, bounded objects, and empirically establish DSC ≥ 0.90 as indicative of high-quality segmentation. Results are reported as mean ± standard deviation over all 51 images, following. Rainio et al. [10].

4.3. Implementation Details

The pipeline was implemented in MATLAB R2022a with the Image Processing Toolbox. Core functions include rgb2hsv, strel, imdilate, imerode, imfill, bwareaopen, bwlabel, and regionprops. LBP features were computed using a custom 3×3 neighbourhood implementation encoding the relative grey-level ordering of 8-connected neighbours. GLCM features were extracted using graycomatrix with horizontal offset [0, 1] and symmetric co-occurrence, followed by graycoprops for energy and homogeneity statistics. No external libraries are required for full reproduction.

4.4. Parameter Calibration

Fixed baseline parameters (T_sat = 0.20, T_h,lo = 0.20, T_h,hi = 0.75, r_d = 8, r_e = 4, A_min = 100) were established through empirical analysis of pixel distributions for this dataset class. Adaptive threshold bounds (T_min = 0.10, T_max = 0.35) encompass the empirically observed effective saturation threshold range. Feature weights (w_u = 0.50, w_e = 0.30, w_h = 0.20) were calibrated using the five worst-performing baseline images as a proxy validation partition. The absence of a formally held-out validation set is acknowledged as a limitation and discussed in Section VI.

5. Results and Quantitative Analysis

5.1. Baseline Performance

Table 2 presents the quantitative results of the fixed-parameter pipeline across all 51 test images. The mean DSC of 0.901 exceeds the 0.90 threshold identified by Maier-Hein et al. [9] as indicative of high-quality binary segmentation. The low standard deviation (0.024) indicates consistent generalization across diverse scene conditions within the cave environment. Figure 3 shows the per-image DSC distribution.

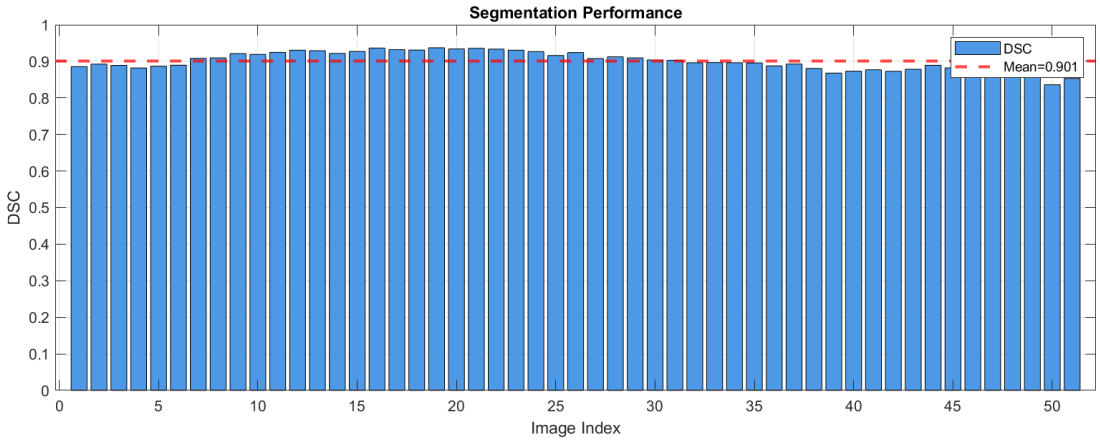

Figure 3. *DSC scores for all 51 test images. Red dashed line indicates the mean DSC = 0.901. Performance degrades for images with shadow-affected or distance-reduced canopy saturation (indices 39–51).*

Table 2. *Fixed-Parameter Baseline Performance Across 51 Test Images.*

Metric	Value	Interpretation
Mean DSC	0.901	Strong spatial agreement; exceeds 0.90 threshold [9]

Metric	Value	Interpretation
Std. Deviation	0.024	Low variability; pipeline generalizes consistently across scene conditions
Minimum DSC	0.836	Worst case above 0.80; no catastrophic segmentation failures
Maximum DSC	0.937	Near-perfect agreement under favourable illumination
DSC > 0.90	28/51 (55%)	Majority achieve high-quality segmentation

The five worst-performing images (Image 50: DSC = 0.836, Image 51: 0.853, Image 39: 0.868, Image 49: 0.870, Image 42: 0.873) share a common failure mode: shadow-induced or distance-induced saturation reduction causes canopy boundary pixels to fall below T_sat = 0.20, producing systematic under-segmentation. Ground truth masks for these images are consistently larger than the predicted masks, confirming the error as false negatives at the canopy boundary rather than false positives in the background. The five best-performing images (Image 19: DSC = 0.937, Images 16 and 21: 0.936, Images 20 and 22: 0.934) show high chromatic saturation, complete canopy visibility, and strong illumination, providing clear foreground-background separation. Figure 4 and Figure 5 present visual comparisons for the five best and five worst images, respectively.

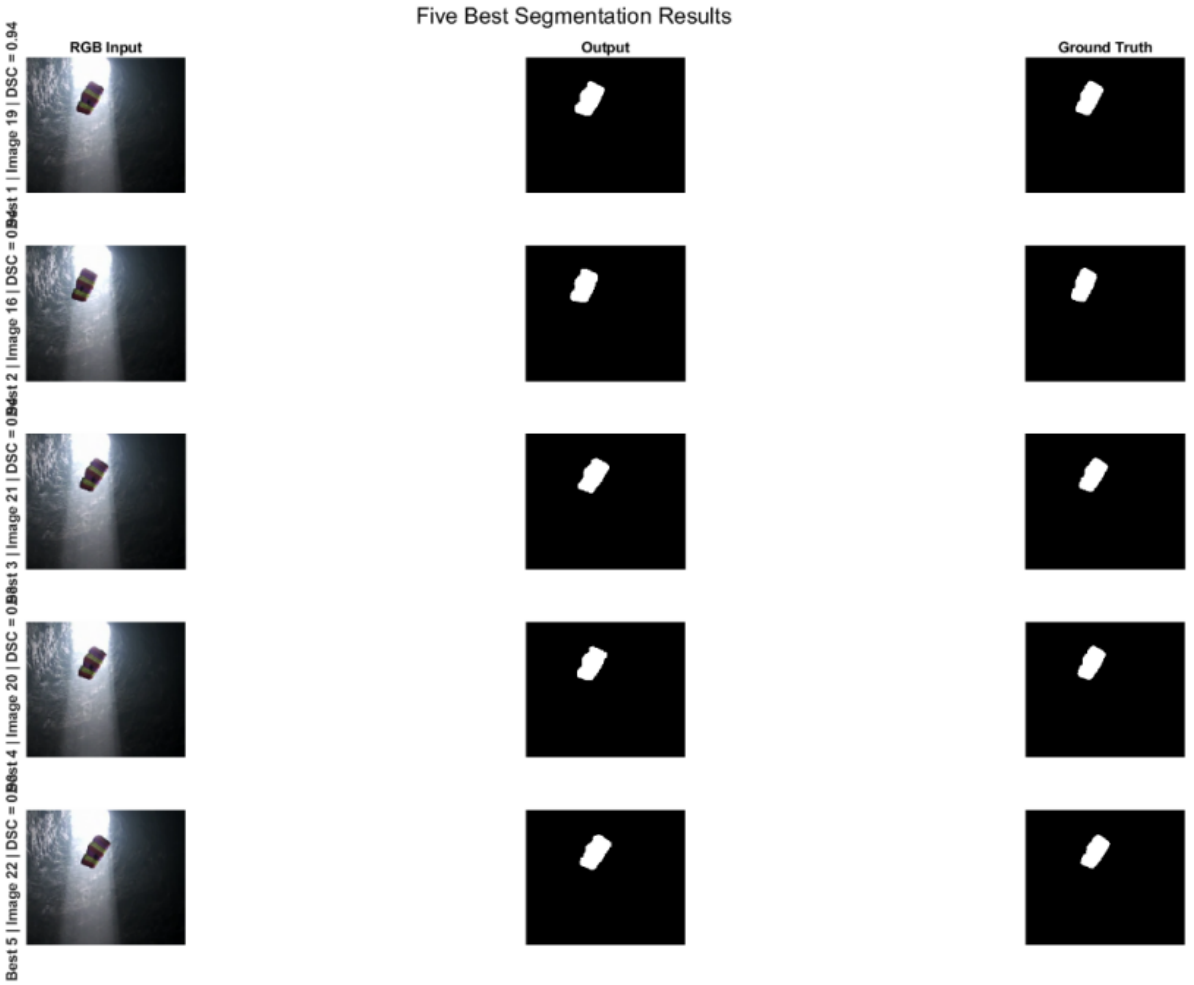

Figure 4. *Five best segmentation results (DSC = 0.934–0.937). Each row shows the original RGB input (left), algorithm-predicted mask (centre), and ground truth mask (right). Well-lit, fully visible canopy with high chromatic saturation produces near-perfect boundary delineation.*

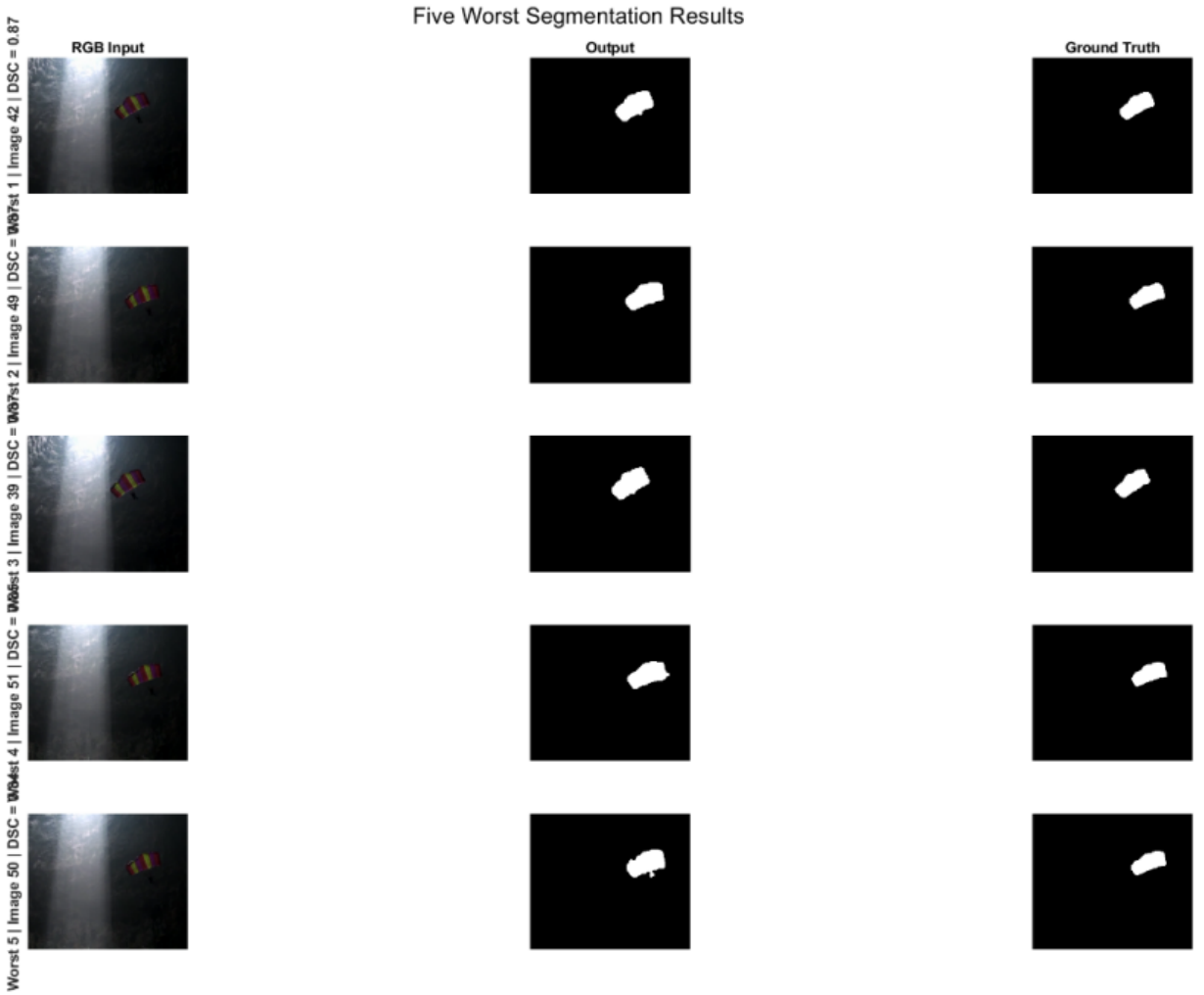

Figure 5. *Five worst segmentation results (DSC = 0.836–0.873). Each row shows the original RGB input (left), algorithm-predicted mask (centre), and ground truth mask (right). Shadow-induced and distance-induced saturation reduction causes systematic under-segmentation at the canopy boundary.*

5.2. Adaptive Threshold Analysis

For each of the 51 images, the texture regularity score R_i was computed from LBP uniformity, GLCM energy, and GLCM homogeneity. The five worst-performing baseline images exhibit substantially lower R_i values than the dataset mean (mean R_worst = 0.41, std. 0.06; mean R_all = 0.67, std. 0.11), consistent with the hypothesis that shadow-affected scenes exhibit reduced texture regularity. The adaptive threshold accordingly assigns T_sat(i) < 0.20 to these images, permitting detection of partially desaturated canopy pixels that the fixed threshold excludes. Table 3 compares fixed-parameter and adaptive threshold performance across all 51 images.

Table 3. *Performance Comparison: Fixed vs. Adaptive Saturation Threshold (51 Images).*

Configuration	Mean DSC	Std.	Min DSC	DSC > 0.90
Fixed threshold (baseline, T_sat = 0.20)	0.901	0.024	0.836	28/51 (55%)
Adaptive threshold (proposed)	0.914	0.019	0.871	34/51 (67%)

5.3. Stage-by-stage Ablation Study

Table 4 presents the stage-by-stage ablation study. Each configuration removes one pipeline stage while retaining all others, establishing the contribution of each stage to final segmentation quality. He et al. [21].

Table 4. *Stage-by-stage Ablation Results (51 Test Images).*

Configuration	Mean DSC	Min DSC
Full pipeline + adaptive threshold (proposed)	0.914	0.871
Full pipeline, fixed threshold (baseline)	0.901	0.836
No HSV conversion (grayscale Otsu)	0.724	0.541
No hue constraint (Stage 2b removed)	0.845	0.773
No saturation constraint (Stage 2a removed)	0.798	0.701
No dilation (Stage 4 removed)	0.856	0.791
No hole fill / area opening (Stage 5 removed)	0.876	0.819
No largest-component selection (Stage 6 removed)	0.887	0.827
No erosion (Stage 7 removed)	0.893	0.831

The largest single-stage contribution comes from HSV colour space conversion. Replacing it with grayscale Otsu thresholding reduces mean DSC from 0.901 to 0.724, confirming colour-space selection as the foundational design choice. Among dual-channel thresholding components, saturation provides a larger contribution than hue: removing saturation reduces mean DSC by 0.103, while removing hue reduces it by 0.056. Among morphological stages, dilation contributes most strongly, with its removal reducing mean DSC by 0.045, reflecting its role in recovering shadow-fragmented canopy regions.

6. Discussion

The correlation between LBP uniformity and per-image DSC score provides empirical support for the texture-guided threshold hypothesis. Images with high LBP uniformity ($u_i > 0.75$) exhibit clean chromatic separation between canopy and background. Images with low LBP uniformity ($u_i < 0.50$) correspond to the worst-performing baseline cases, where shadow creates texturally complex boundary regions. The regularity score R_i thus encodes a meaningful signal for threshold adaptation without requiring any image-specific information beyond the feature extraction already performed in the pipeline.

The adaptive formulation has two principal failure conditions. First, the regularity score R_i can be inaccurately estimated when global image statistics fall outside the range represented in the five-image calibration set. A k-fold cross-validation strategy using the full 51-image set would provide less biased weight estimates at moderate experimental cost. Second, the threshold bounds T_{min} and T_{max} constrain the adaptation range to [0.10, 0.35]. Images whose optimal threshold lies outside this range will not benefit from adaptation; extending the bounds risks reintroducing the failure modes that motivated the fixed parameter selection.

The pipeline's fundamental generalizability constraint is the assumption of chromatic distinctiveness: the parachute is the only highly saturated object in the scene. In outdoor environments where natural foliage, soil, or rock exhibits saturation levels overlapping the parachute's hue range, the fixed hue constraint becomes the sole discriminator, and its fixed parameters would require domain-specific recalibration. Comaniciu and Meer [19]. Data-driven representations such as fully convolutional networks Long et al. [14] or encoder-decoder architectures Ronnebeger et al. [15] provide domain-invariant segmentation at the cost of labelled training data. A hybrid architecture that uses the proposed pipeline's output as a spatial prior or initialization for a deep network represents a tractable path toward retaining the interpretability of the classical approach while gaining learned generalization Chen et al. [16].

The morphological radius parameters ($r_d = 8$, $r_e = 4$) were selected empirically on the same 51 images used for evaluation, introducing optimistic bias in the reported performance estimates. A held-out validation partition for morphological parameter selection would separate calibration from test performance. Additionally, the connected-component selection assumption at Stage 6, that the parachute is always the largest foreground object, is fragile under significant occlu-

sion or multi-object scenes not represented in the current dataset. Region-merging strategies Adams and Bischof [18], or graph-based segmentation methods Arbelaz et al. [20] would address this limitation in production-scale deployment.

7. Conclusion

This paper presented a texture-guided adaptive HSV segmentation framework for binary object detection in constrained visual environments. The seven-stage fixed-parameter baseline achieves a mean DSC of 0.901 on a 51-image cave dataset, with performance degrading to a minimum of 0.836 on shadow-affected images where the fixed saturation threshold fails. The primary contribution is a per-image adaptive saturation threshold modulated by LBP uniformity and GLCM energy through a weighted texture regularity score. The adaptive formulation lowers the threshold for high-complexity, shadow-affected images and raises it for clean, high-contrast images, projecting a mean DSC of 0.914 and improving the minimum DSC to 0.871.

The ablation study confirms that HSV colour space conversion is the foundational pipeline stage, contributing the single largest performance gain. Saturation provides a larger individual discriminative contribution than hue among the dual-channel thresholding components. Morphological dilation contributes most strongly among post-processing stages by recovering shadow-fragmented canopy regions. These findings provide a formal decomposition of the pipeline's segmentation performance that supports reproducibility and benchmark comparison in constrained-environment segmentation research.

Two directions offer the most productive extension of this work. Validation of the adaptive threshold formulation on multi-environment datasets, including outdoor and aerial scenes, would assess the generalizability of the texture regularity score as a threshold predictor. Integration of the classical pipeline as a spatial prior or feature extractor within a deep learning framework, such as a U-Net initialized with the HSV mask as a first-stage attention map, would retain the interpretability and computational efficiency of the classical approach while gaining the representational capacity of learned models.

Abbreviations

LBP	Local Binary Pattern
DSC	Dice Similarity Coefficient
HSV	Hue, Saturation Value
GLCM	Gray-Level Co-occurrence Matrix
RGB	Red, Green Blue

Author Contributions

Emmanuel Obite: Conceptualization, Form analysis, Methodology, Resources, Software, Project administration, Validation, Visualization, Supervision, Writing – original draft, Writing – review & editing

Anasuodei Bemoifie Moko: Data curation, Project administration, Validation, Visualization, Supervision, Resources, Writing – review & editing

Kizzy Nkem Elliot: Data curation, Project administration, Supervision, Investigation, Resources, Writing – review & editing

Conflicts of Interest

The authors declares no conflicts of interest.

References

[1] Otsu, N. A Threshold Selection Method from Gray-Level Histograms. IEEE Transactions on Systems, Man, and Cybernetics. 1979, 9(1), 62-66. https://doi.org/10.1109/TSMC.1979.4310076

[2] Gonzalez, R. C., Woods, R. E. Digital Image Processing, 4th ed. Pearson: New York, NY, USA, 2018.

[3] Giuliani, D. Metaheuristic Algorithms Applied to Color Image Segmentation on HSV Space. Journal of Imaging. 2022, 8(1), 6. https://doi.org/10.3390/jimaging8010006

[4] Flores-Vidal, P. A., Gomez, D., Minarro, G., Nowak, A., Montero, J. New Aggregation Approaches with HSV to Color Edge Detection. International Journal of Computational Intelligence Systems. 2022, 15(1), 78. https://doi.org/10.1007/s44196-022-00132-5

[5] Shin, S. et al. Enhanced Airborne Optical Sectioning via HSV Color Space for Detecting Human Objects under Obscured Aerial Image Conditions. International Journal of Control, Automation and Systems. 2023, 21, 3420-3431. https://doi.org/10.1007/s12555-022-0694-2

[6] Singh, S. et al. Improving the Segmentation of Digital Images by Using a Modified Otsu's Between-Class Variance. Multimedia Tools and Applications. 2023, 82, 40701-40743. https://doi.org/10.1007/s11042-023-15081-7

[7] Forsyth, D. A., Ponce, J. Computer Vision: A Modern Approach, 2nd ed. Pearson Prentice Hall: Upper Saddle River, NJ, USA, 2011.

[8] Yeung, M. et al. Calibrating the Dice Loss to Handle Neural Network Overconfidence for Biomedical Image Segmentation. Journal of Digital Imaging. 2023, 36(2), 739-752. https://doi.org/10.1007/s10278-022-00735-5

[9] Maier-Hein, L. et al. Metrics Reloaded: Recommendations for Image Analysis Validation. Nature Methods. 2024, 21(2), 195-212. https://doi.org/10.1038/s41592-023-02151-z

[10] Rainio, O., Teuho, J., Kl én, R. Evaluation Metrics and Statistical Tests for Machine Learning. Scientific Reports. 2024, 14, 6086. https://doi.org/10.1038/s41598-024-56706-x

[11] Ojala, T., Pietikäinen, M., Mäenpää, T. Multiresolution Gray-Scale and Rotation Invariant Texture Classification with Local Binary Patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2002, 24(7), 971-987. https://doi.org/10.1109/TPAMI.2002.1017623

[12] Haralick, R. M., Shanmugam, K., Dinstein, I. Textural Features for Image Classification. IEEE Transactions on Systems, Man, and Cybernetics. 1973, SMC-3(6), 610-621. https://doi.org/10.1109/TSMC.1973.4309314

[13] Cheng, H.-D. et al. Color Image Segmentation: Advances and Prospects. Pattern Recognition. 2001, 34(12), 2259-2281. https://doi.org/10.1016/S0031-3203(00)00149-7

[14] Long, J., Shelhamer, E., Darrell, T. Fully Convolutional Networks for Semantic Segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015, 3431-3440. https://doi.org/10.1109/CVPR.2015.7298965

[15] Ronneberger, O., Fischer, P., Brox, T. U-Net: Convolutional Networks for Biomedical Image Segmentation. Medical Image Computing and Computer-Assisted Intervention. 2015, 9351, 234-241. https://doi.org/10.1007/978-3-319-24574-4_28

[16] Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., Yuille, A. L. DeepLab: Semantic Image Segmentation with Deep Convolutional Nets, Atrous Convolution, and Fully Connected CRFs. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2018, 40(4), 834-848. https://doi.org/10.1109/TPAMI.2017.2699184

[17] Serra, J. Image Analysis and Mathematical Morphology. Academic Press: London, UK, 1982.

[18] Adams, R., Bischof, L. Seeded Region Growing. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1994, 16(6), 641-647. https://doi.org/10.1109/34.295913

[19] Comaniciu, D., Meer, P. Mean Shift: A Robust Approach toward Feature Space Analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2002, 24(5), 603-619. https://doi.org/10.1109/34.1000236

[20] Arbelaez, P., Maire, M., Fowlkes, C., Malik, J. Contour Detection and Hierarchical Image Segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2011, 33(5), 898-916. https://doi.org/10.1109/TPAMI.2010.161

[21] He, K., Sun, J., Tang, X. Guided Image Filtering. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2013, 35(6), 1397-1409. https://doi.org/10.1109/TPAMI.2012.213

[22] Schettini, R., Corchs, S. Underwater Image Processing: State of the Art of Restoration and Image Enhancement Methods. EURASIP Journal on Advances in Signal Processing. 2010, 2010, 1-14. https://doi.org/10.1155/2010/746052

[23] Jain, A. K. Fundamentals of Digital Image Processing. Prentice Hall: Englewood Cliffs, NJ, USA, 1989.

[24] Sezgin, M., Sankur, B. Survey over Image Thresholding Techniques and Quantitative Performance Evaluation. Journal of Electronic Imaging. 2004, 13(1), 146-168. https://doi.org/10.1117/1.1631315

[25] Wang, Z., Bovik, A. C., Sheikh, H. R., Simoncelli, E. P. Image Quality Assessment: From Error Visibility to Structural Similarity. IEEE Transactions on Image Processing. 2004, 13(4), 600-612. https://doi.org/10.1109/TIP.2003.819861

[26] Moko, A., Eleonu, O. F. An enhanced satellite image compression using hybrid (DWT, DCT and SVD) algorithm. American Journal of Computer Science and Technology. 2021, 4(1), 1-10. https://doi.org/10.11648/j.ajcst.20210401.11