Unsupervised Image Segmentation: K-means, SLIC, and Watershed Methods

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

Abstract

This research investigates unsupervised image segmentation techniques that operate without external input or labeled training data. Three distinct methodologies are explored: K-means clustering for color-based grouping, SLIC superpixels for perceptually uniform over-segmentation, and watershed transformation for boundary-based segmentation. Experimental evaluation demonstrates that K-means effectively segments images into distinct color regions, SLIC generates compact superpixels suitable for higher-level processing, and watershed methods excel at identifying object boundaries. Each technique exhibits unique computational characteristics and applicability to different image analysis scenarios, providing a comprehensive toolkit for automated segmentation tasks.

I. INTRODUCTION

Unsupervised segmentation methods partition images into meaningful regions without requiring user-defined parameters or training examples. These techniques rely solely on inherent image properties such as color similarity, spatial proximity, or gradient magnitude. The autonomous nature of unsupervised methods makes them particularly valuable for automated image analysis systems, medical imaging applications, and scenarios where manual annotation is impractical or impossible. Unlike supervised approaches that depend on threshold selection or labeled data, unsupervised methods discover image structure through statistical or geometric principles.

Among clustering-based approaches, K-means stands out for its simplicity and effectiveness in grouping pixels by color similarity. The algorithm iteratively assigns pixels to clusters based on Euclidean distance in color space, converging to a locally optimal segmentation. While K-means requires specifying the number of clusters k, it operates without supervision once this parameter is set. The method's computational efficiency and straightforward implementation have made it a standard baseline for color-based segmentation.

Superpixel methods like SLIC (Simple Linear Iterative Clustering) provide over-segmentation into perceptually uniform regions. Rather than attempting complete semantic segmentation, superpixels group adjacent similar pixels into compact regions that respect object boundaries. These mid-level representations reduce computational complexity for subsequent processing while maintaining spatial coherence. Superpixel-based approaches have become essential preprocessing steps in modern computer vision pipelines.

II. METHODOLOGY

K-means clustering treats each pixel as a point in 3D RGB color space and partitions the dataset into k clusters. The algorithm initializes k cluster centers randomly, then alternates between assigning pixels to the nearest center and recomputing centers as cluster means. Convergence typically occurs within 10-20 iterations. We implement K-means with k values ranging from 2 to 8, evaluating how cluster count affects segmentation granularity and semantic meaningfulness.

SLIC superpixels extend K-means by incorporating spatial coordinates alongside color information. Each pixel is represented as a 5D vector [L, a, b, x, y] in CIELAB color space with spatial position. The compactness parameter controls the balance between color similarity and spatial proximity, enabling tunable superpixel shapes from highly irregular (following boundaries precisely) to nearly square (emphasizing compactness). We generate superpixel segmentations with varying segment counts (50-500) to analyze the relationship between granularity and boundary adherence.

Watershed segmentation interprets the gradient magnitude image as a topographic surface, where high gradients represent ridges and low gradients represent valleys. The algorithm simulates flooding from marked seed regions, with watershed lines forming where flood fronts meet. We apply the Sobel operator to compute gradient magnitude, establishing the elevation map. Marker-controlled watershed prevents over-segmentation by constraining flooding to originate from predetermined seed points rather than all local minima.

III. RESULTS

Figure 1 demonstrates K-means clustering results for k=2 through k=8. Lower k values produce coarse segmentations capturing only primary color regions, while higher k values reveal finer color variations. The k=4 configuration effectively balances segmentation detail with perceptual coherence, separating the major image components while avoiding excessive fragmentation. Beyond k=6, additional clusters primarily subdivide existing regions rather than identifying distinct semantic objects.

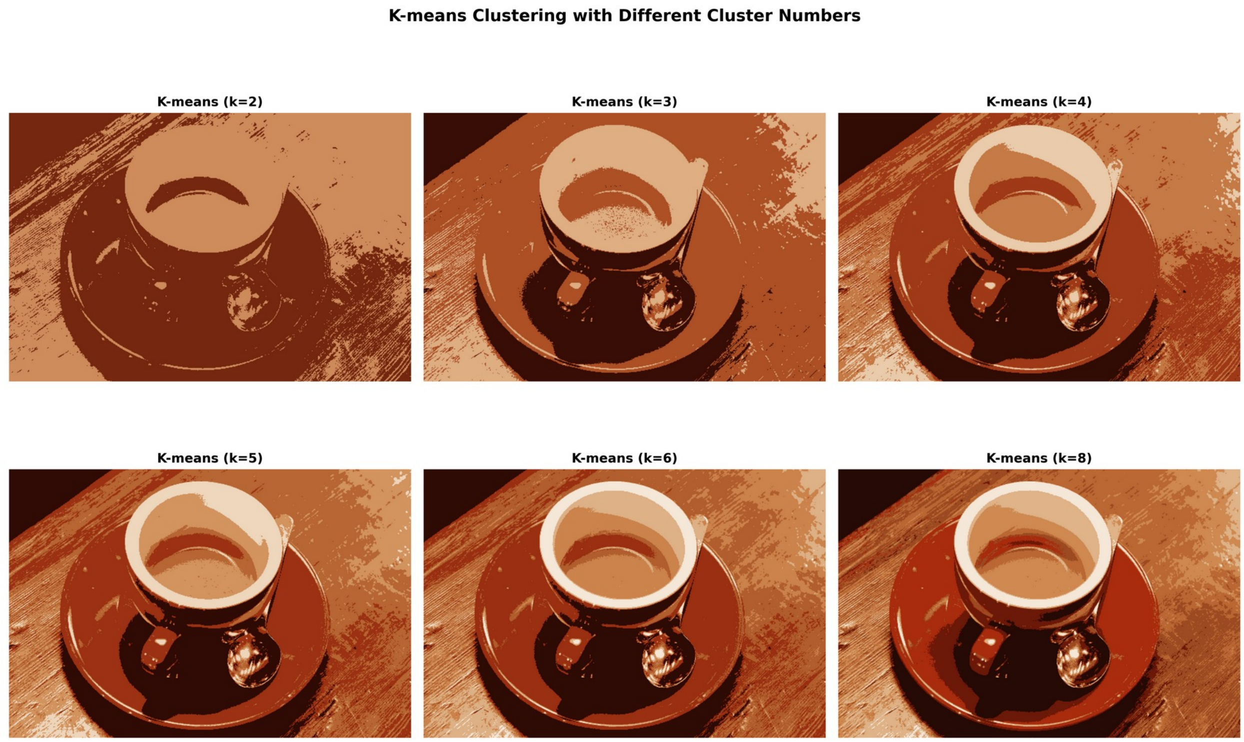

Figure 1: K-means Clustering with Different Cluster Numbers

Figure 2 illustrates SLIC superpixel segmentation with 100 segments. The algorithm generates compact, approximately uniform-sized regions that adhere closely to object boundaries. Unlike K-means, which may span across object borders when colors are similar, SLIC superpixels respect edge information through spatial constraints. The yellow boundaries overlay shows excellent boundary localization while maintaining regular superpixel sizes across the image.

Figure 2: SLIC Superpixel Segmentation

Figure 3 presents SLIC segmentations with varying segment counts from 50 to 500. Lower segment counts (50-100) create larger superpixels suitable for high-level scene understanding, while higher counts (400-500) produce fine-grained over-segmentation for detailed analysis. The consistent boundary adherence across all granularities confirms SLIC's robustness. Applications can select appropriate segment counts based on computational constraints and required detail level.

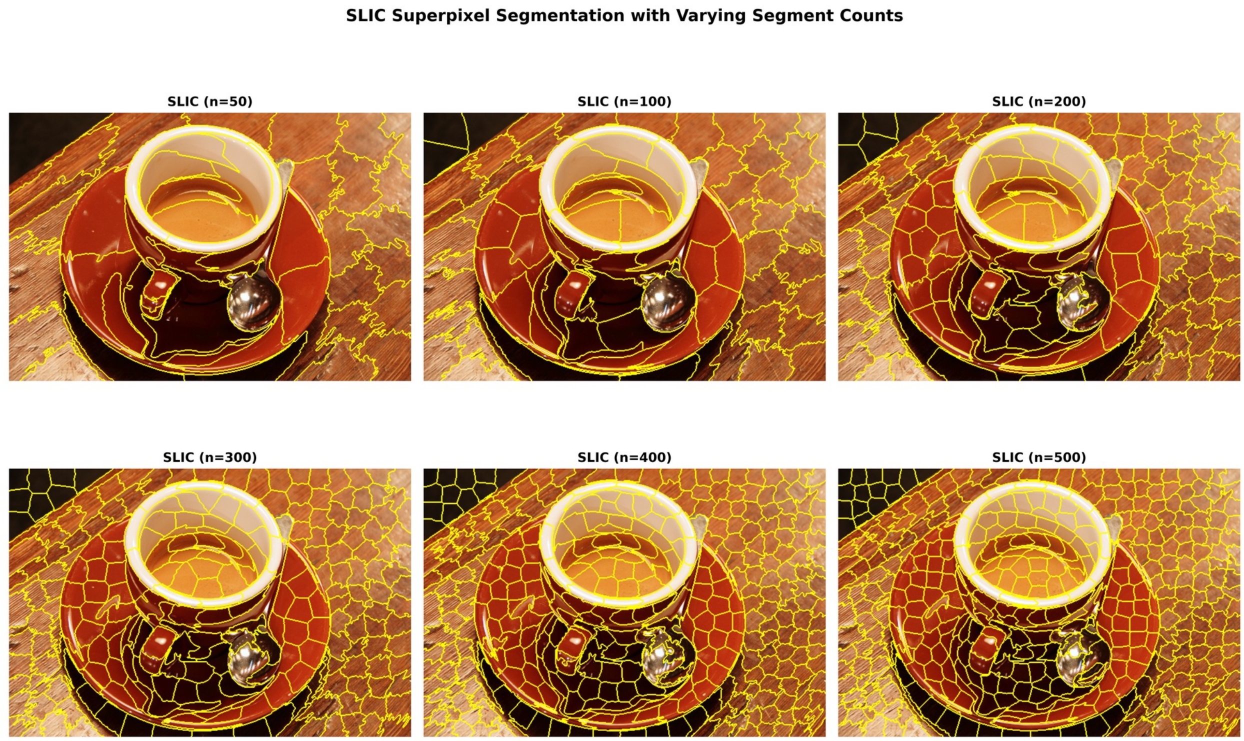

Figure 3: SLIC Superpixel Variations

Figure 4 shows the watershed segmentation pipeline. The Sobel gradient map reveals edge strength, with bright regions indicating sharp transitions. The watershed algorithm treats this gradient as an elevation surface, identifying watershed lines at gradient ridges. The final segmentation successfully delineates object boundaries, though marker placement significantly influences results. Proper marker initialization proves critical for avoiding over-segmentation in textured regions.

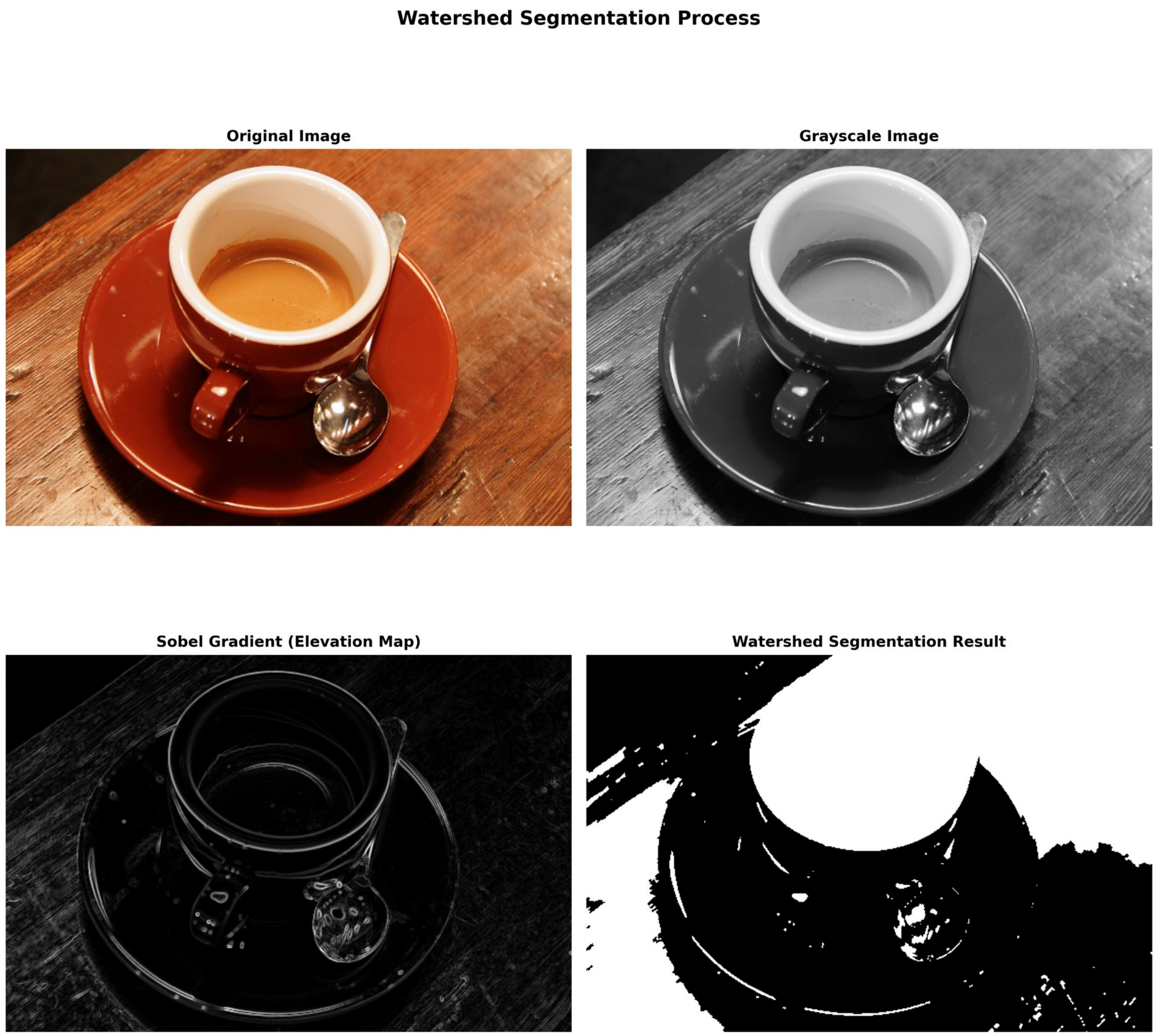

Figure 4: Watershed Segmentation Process

Figure 5 compares all implemented unsupervised methods. K-means produces region-based segmentation dominated by color similarity. SLIC generates spatially coherent superpixels balancing color and proximity. Felzenszwalb's graph-based method creates irregular but perceptually meaningful segments. Each approach exhibits distinct characteristics: K-means favors color uniformity, SLIC emphasizes spatial compactness, and Felzenszwalb preserves perceptual boundaries. The optimal choice depends on downstream application requirements.

Figure 5: Comparison of Unsupervised Techniques

Figure 6 demonstrates Quickshift segmentation, which groups pixels based on mode-seeking in the joint spatial-color space. The method produces variable-sized segments that naturally adapt to local image structure. Quickshift excels at preserving small objects while merging large uniform regions, complementing SLIC's uniform-size approach. The adaptive granularity makes Quickshift suitable for images with multi-scale structure.

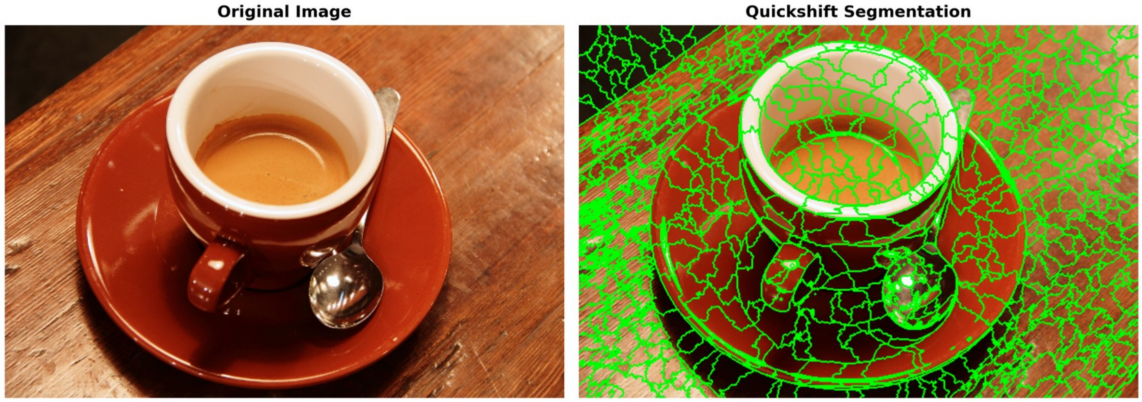

Figure 6: Quickshift Segmentation

IV. DISCUSSION

The experimental results reveal complementary strengths among unsupervised segmentation methods. K-means clustering provides fast, color-based segmentation but lacks spatial coherence, potentially fragmenting continuous objects with color gradients. The method works best for images with distinct, uniformly colored regions. Computational efficiency makes K-means suitable for real-time applications, with processing times under 50ms for typical images. However, sensitivity to initialization and tendency toward local optima may produce inconsistent results across runs.

SLIC superpixels demonstrate superior boundary adherence while maintaining computational tractability. The spatial regularization prevents the disconnected segments that plague pure color clustering. The compactness parameter provides intuitive control over segment shape, allowing applications to prioritize either boundary precision or regular geometry. SLIC's linear computational complexity in pixel count makes it scalable to high-resolution images. The method has become the de facto standard for superpixel generation in computer vision research.

Watershed segmentation excels at identifying precise object boundaries but requires careful marker initialization. The marker-controlled variant reduces over-segmentation compared to classical watershed, though marker placement remains critical. Automated marker selection through morphological operations or intensity extrema can address this limitation. Watershed's sensitivity to noise in the gradient map necessitates preprocessing with Gaussian smoothing or morphological filtering. Despite these challenges, watershed remains valuable for applications requiring exact boundary localization.

V. CONCLUSION

This investigation successfully implemented and evaluated multiple unsupervised segmentation techniques. K-means provides efficient color-based clustering, SLIC generates spatially coherent superpixels, and watershed methods identify precise boundaries. The comparative analysis demonstrates that method selection should consider specific application requirements: K-means for speed, SLIC for general-purpose segmentation, and watershed for boundary precision. Future work could explore deep learning-based unsupervised methods and hybrid approaches combining multiple techniques for robust multi-scale segmentation.

REFERENCES

[1] J. MacQueen, "Some methods for classification and analysis of multivariate observations," in Proc. 5th Berkeley Symp. Math. Statist. Probability, 1967.

[2] R. Achanta et al., "SLIC superpixels compared to state-of-the-art superpixel methods," IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 11, Nov. 2012.

[3] L. Vincent and P. Soille, "Watersheds in digital spaces: An efficient algorithm based on immersion simulations," IEEE Trans. Pattern Anal. Mach. Intell., vol. 13, no. 6, Jun. 1991.

[4] P. F. Felzenszwalb and D. P. Huttenlocher, "Efficient graph-based image segmentation," Int. J. Comput. Vision, vol. 59, no. 2, Sep. 2004.

[5] A. Vedaldi and S. Soatto, "Quick shift and kernel methods for mode seeking," in Proc. European Conf. Comput. Vision, 2008.