Image Segmentation Using Clustering Techniques

CV_Assignment-2.ipynb

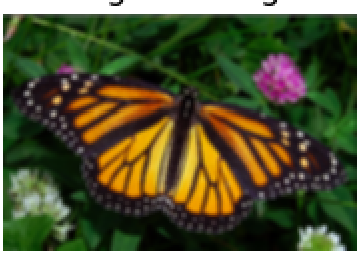
Objective:

To implement and compare two clustering techniques, Ratio-Cut based spectral clustering and K-means clustering, for the task of image segmentation. The goal was to understand and visualize the effectiveness of each method in segmenting images into predefined numbers of clusters (3 and 6 clusters).

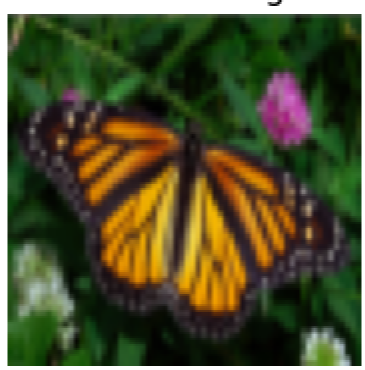
Preprocessing:

Images were resized to 64x64 pixels to reduce computational complexity and ensure uniformity across the dataset.

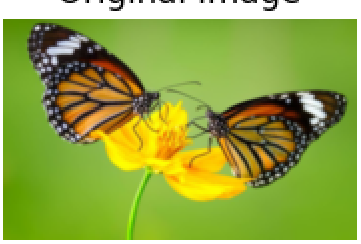
Original Image



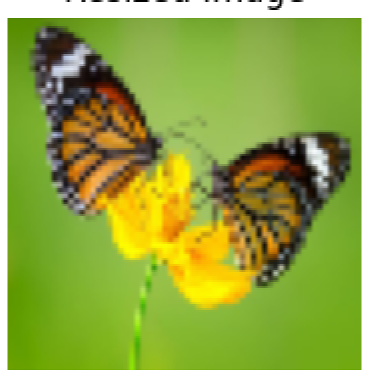
Resized Image



Original Image



Resized Image



Ratio-Cut Based Spectral Clustering:

- Graph Representation: Each pixel was treated as a node, with edges connecting to all other pixels. Edge weights were defined based on the Euclidean distance between pixel intensities.
- Laplacian Matrix: Computed from the degree and adjacency matrices of the graph.
- Eigenvalue Decomposition: Used to find the smallest eigenvectors, which served as features for clustering.
- K-means Clustering: Applied to the eigenvector space to segment the image based on spectral features.

K-means Clustering:

- Directly applied to the flattened RGB values of the images.
- Utilized to segment images based purely on color similarities, without considering spatial or relational information as in spectral clustering.

Visualization and Results:

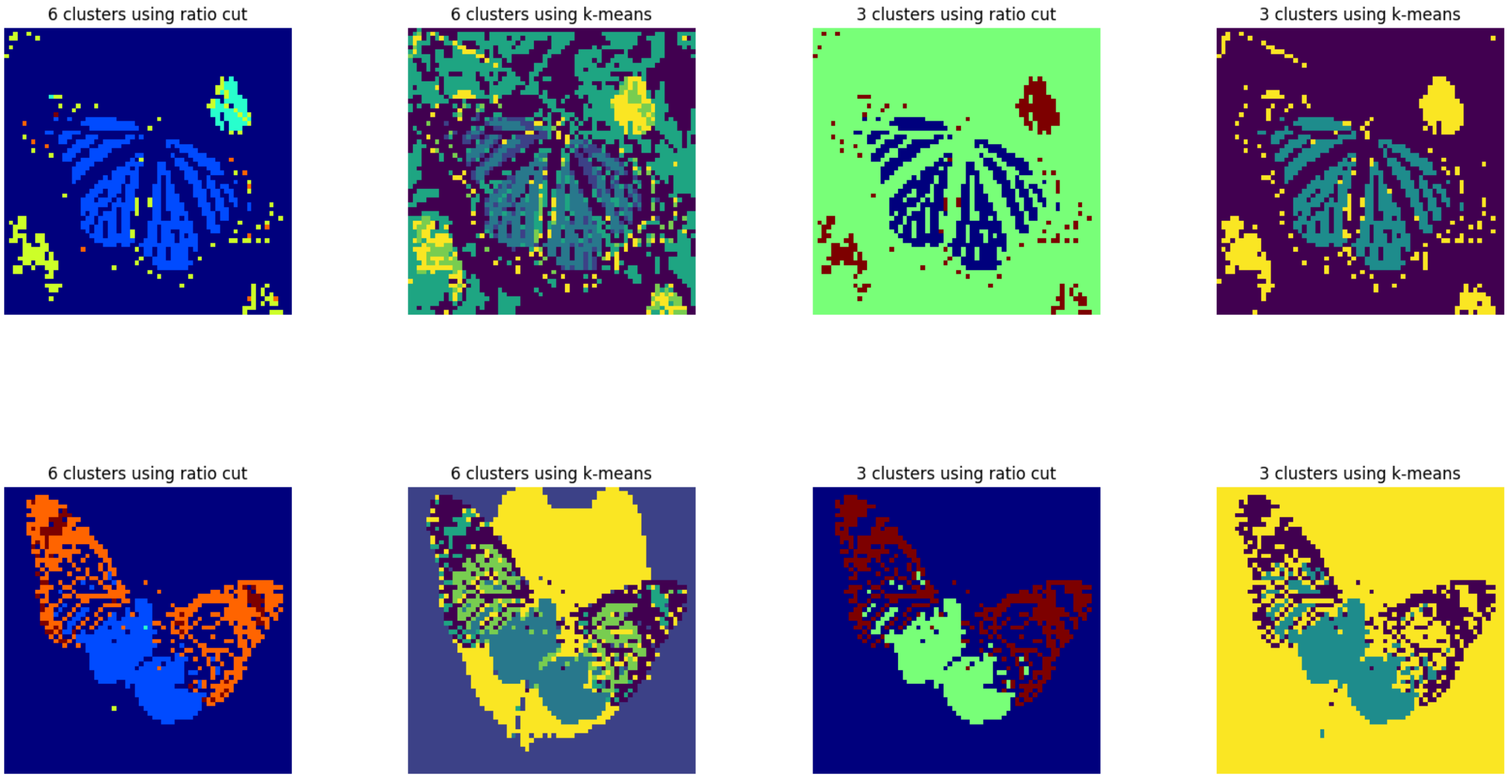


Fig 1 : without Normalizing Laplacian and EigenVectors sigma = 25.

Image	K-means Clustering 6 clusters	Spectral Clustering 6 clusters	K-means Clustering 3 clusters	Spectral Clustering 3 clusters
Image1	0.47366588198243287	0.6452398527701242	0.6613227774901779	0.6785527094108208
Image2	0.5256502548921123	0.5719931694504341	0.6027144724775256	0.6055509896798773

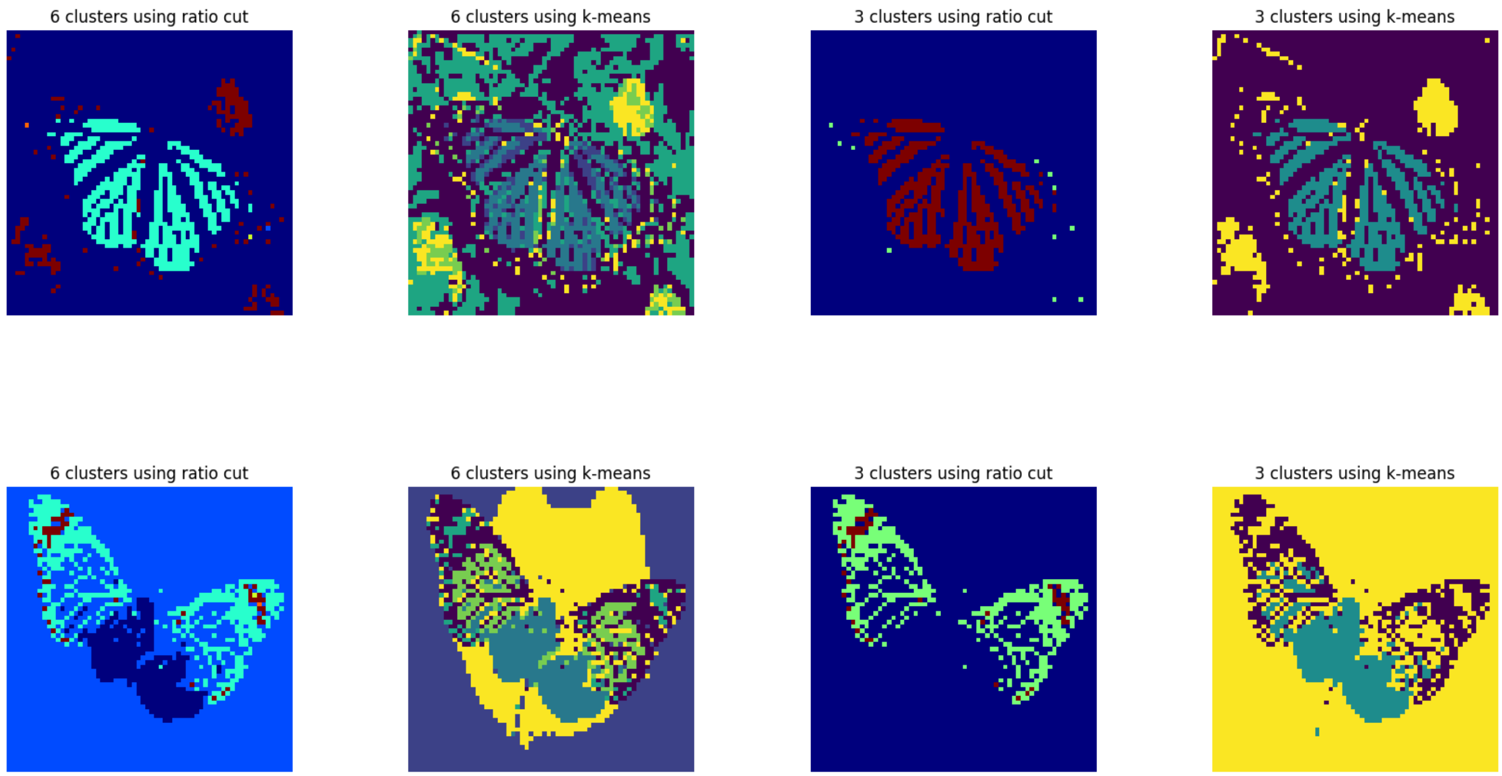


Fig 2 : without Normalizing Laplacian and EigenVectors sigma = 40.

Image	K-means Clustering 6 clusters	Spectral Clustering 6 clusters	K-means Clustering 3 clusters	Spectral Clustering 3 clusters
Image1	0.47366588198243287	0.6613449499623232	0.6213227774901779	0.6665472622683039
Image2	0.5256502548921123	0.6070923351094775	0.6020144724775256	0.6027130695845833

Fine Tuning Sigma value we got the following results:

Sigma	Silhouette Score
10.0	0.48426049825969175
20.0	0.5557093466893025
30.0	0.5893767275498243
50.0	0.5906999229833951
40.0	**0.6070923351094775**

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Silhouette Score for K-means Clustering 6 clusters: 0.5256502548921123
Silhouette Score for Spectral Clustering 6 clusters: 0.6070923351094775
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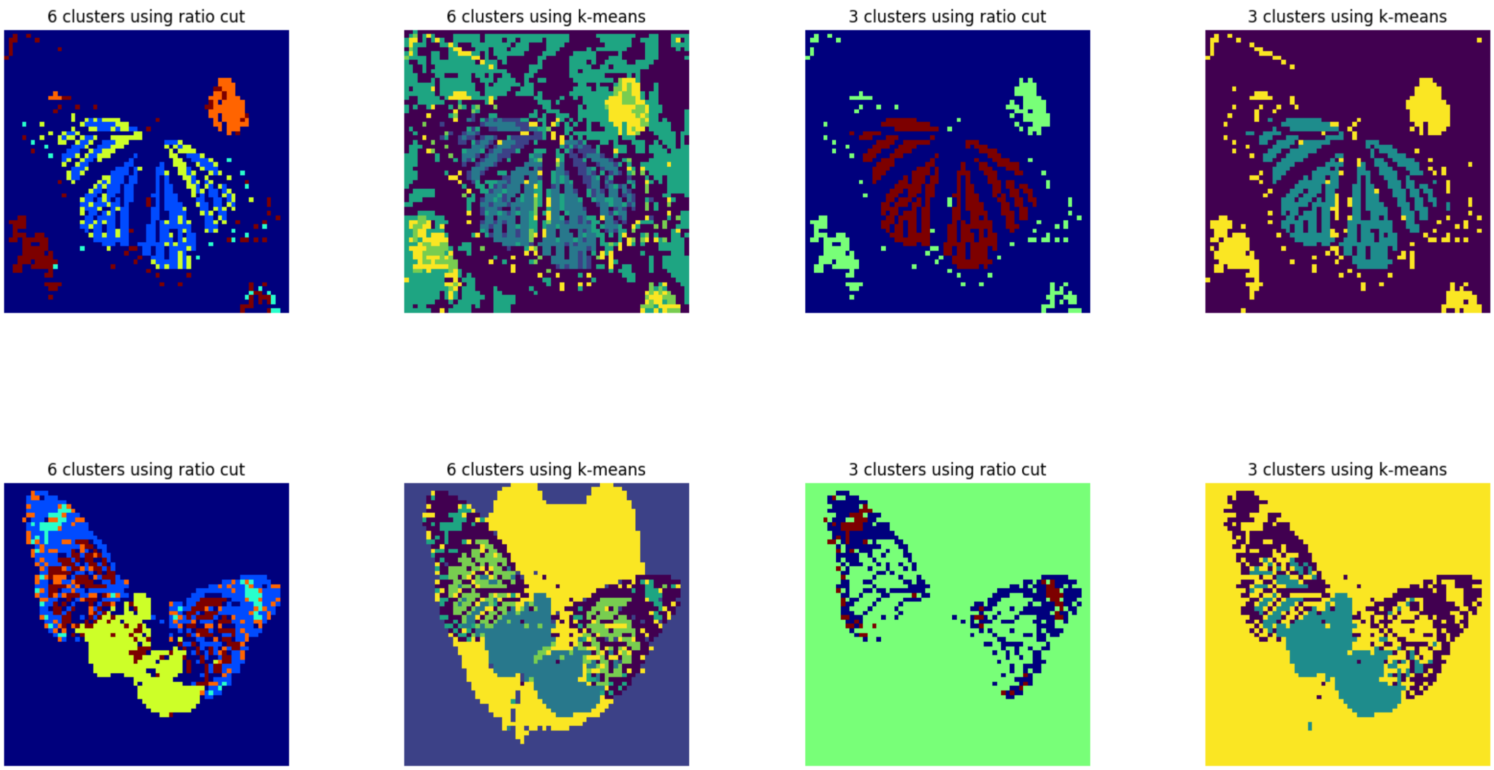

Fig 3 : Normalizing Laplacian and unnormalized EigenVectors sigma = 20.

Image	K-means Clustering 6 clusters	Spectral Clustering 6 clusters	K-means Clustering 3 clusters	Spectral Clustering 3 clusters
Image1	0.47366588198243287	0.568337774536052	0.6613227774901779	0.6645038518326882
Image2	0.5256502548921123	0.53993280315558	0.6027144724775256	0.5898114717755776

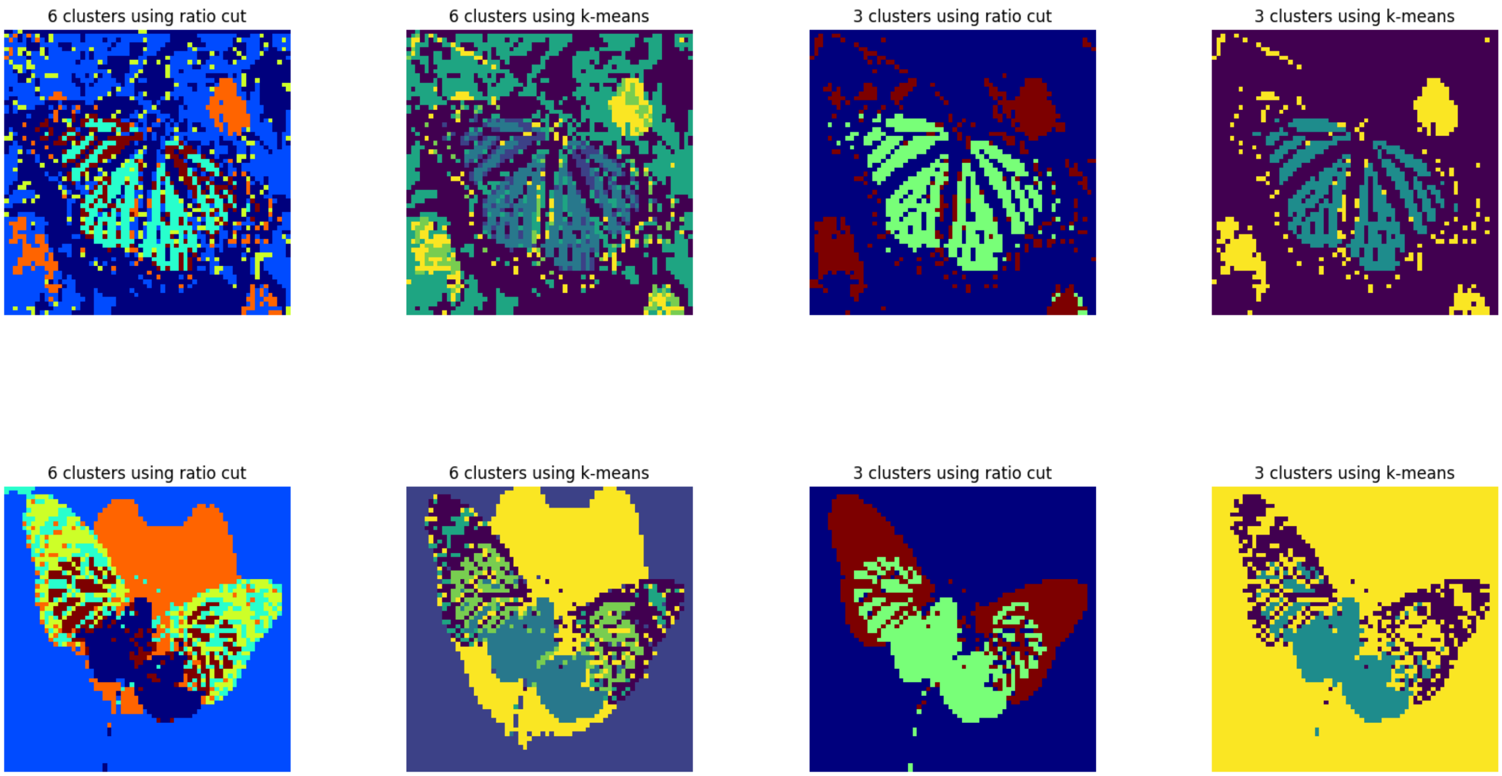

Fig 4 : Normalizing Laplacian and normalized EigenVectors sigma = 20.

Analysis of Segmentation Results

Image 1 Segmentation (Butterfly with Greenery Background)

6 Clusters:

- Spectral Clustering: Provides a segmentation that respects the boundaries of the butterfly quite well, delineating the wings from the body and partially from the background. However, there's some mixing with background colors likely due to the butterfly's edges' proximity to the colors of the leaves.
- K-means Clustering: Results in a less coherent segmentation with significant noise. The method captures multiple colors within the butterfly but fails to maintain clear separation from the background, indicating a segmentation largely driven by color intensity.

3 Clusters:

- Spectral Clustering: Maintains a decent outline of the butterfly. The reduced number of clusters leads to larger, more unified segments, with the background largely separated from the butterfly.
- K-means Clustering: The segmentation simplifies the image significantly, merging the butterfly with the background, making it less distinguishable. The method prioritizes large areas of color, losing finer details.

Image 2 Segmentation (Two Butterflies on a Flower)

6 Clusters:

- Spectral Clustering: Manages to segregate the two butterflies effectively and separate them from the flower, indicating a capability to discern distinct shapes within the image.
- K-means Clustering: Shows a chaotic segmentation with the butterflies not distinctly separated and parts of them blending into the background, suggesting a challenge with complex backgrounds.

3 Clusters:

- Spectral Clustering: Even with fewer clusters, spectral clustering retains the separation of the butterflies from the background. The shape of the butterflies remains somewhat recognizable.
- K-means Clustering: Significantly oversimplifies the image, with the butterflies' shapes losing definition against the background. The method's color-centric approach results in a loss of detail.

Overall Insights

- Segmentation Quality: Spectral clustering is more consistent in preserving the integrity and recognizability of the objects within the images across both 6-cluster and 3-cluster configurations. K-means clustering seems more prone to fragmentation and is influenced more by color variations rather than object continuity.
- Color and Shape Differentiation: The results suggest spectral clustering is better at differentiating between shapes and colors, likely due to its use of the image's structural information. K-means clustering works well when colors are distinct and well-separated but struggles with subtler color gradients and similar color regions.

References:

- https://www.geeksforgeeks.org/ml-spectral-clustering/
- https://people.csail.mit.edu/dsontag/courses/ml14/notes/Luxburg07_tutorial_spectral_clustering.pdf
- https://scikit-learn.org/
- https://pypi.org/project/opencv-python/