Taha Khudher(takh2100) week 4 PM.

Clustering and Segmentation.

Code

4.1 K-means algorithm

$$\min_{\mu,y} \sum_i \|x_i - \mu_{y_i}\|^2$$

Assumptions:

- The points are assumed to form clusters that are approximately spherical.
- Clusters should have similar variances
- Each cluster is modeled as have a normal distribution with same standard deviation across all dimensions.
- The number of clusters k is known.

The figure below shows the first iteration for the calculation. The second iteration was done on a calculator with the new centroids but the centroids don’t change after the second iteration meaning that the algorithm has converged.

$$\min_{\mu, y} \sum_i \| x_i - \mu_{y_i} \|^2$$

Cluster	Point x, y	Euc Distance to [1,1.5]	Distance to (3, 1)
C1	(0, 0.5)	$\sqrt{(0-1)^2 + (0.5-1.5)^2} \approx 1.41$	$\sqrt{(0-3)^2 + (0.5-1)^2} = 3.04$
C1	(0, 0.75)	$\sqrt{(0-1)^2 + (0.75-1.5)^2} = 1.26$	$\sqrt{(0-3)^2 + (0.75-1)^2} = 3.02$
C1	(1, 1)	$\sqrt{(1-1)^2 + (1-1.5)^2} = 0.5$	$\sqrt{(1-3)^2 + (1-1)^2} = 2$
C1	(1.25, 0.4)	$\sqrt{(1.25-1)^2 + (0.4-1.5)^2} = 1.1$	$\sqrt{(1.25-3)^2 + (0.4-1)^2} = 1.85$
C1	(1.5, 0.7)	0.9	1.54
C2	(2.5, 1)	1.58	0.5
C2	(3, 2)	2.06	1.0
C_2	(4, 1.5)	3	1.12
C_2	(4, 2.5)	3.16	1.80
C_2	(5, 2)	4.03	2.24

New centroids = mean of C1 points and C2 points

$$C_1 = \left(\frac{0+0+1+1.25+1.5}{5}, \frac{0.5+0.75+1+0.4+0.7}{5} \right) = (0.75, 0.67)$$

$$C_2 = \left(\frac{2.5+3+4+4+5}{5}, \frac{1+2+1.5+2.5+2}{5} \right) = (3.7, 1.8)$$

4.2 Classification Algorithm

Algorithm	Description	Application	Pros	Cons
KNN	Classifies based on majority vote k closets points	Handwritten digit recognition, image retrieval	Simple, no training required, works well with small datasets.	Slow for large datasets, sensitive to irrelevant features.
K-Means Clustering	Groups similar data points and assigns class labels based on proximity	Image segmentation, object detection.	Fast and simple, good for exploratory analysis	Requires predefined k, struggles with irregular shapes.
Support Vector Machines	Finds a hyperplane that maximally separates classes, Can use kernels for non-linear data.	Face Detection, object recognition.	Works well with high-dimensional data, robust to overfitting.	COmputationally expensive for large datasets, sensitive to parameter tuning.
Decision Trees	Splits data based on feature thresholds, forming a treen structure.	Medical imaging, object recognition.	Fast inference, easy to interpret	Prone to overfitting, especially with deep trees.
Random Forest	Ensemble of decision trees that vote for the best class.	Image classification, defect detection.	Handles missing data well, less overfitting than a single decision tree	Can be slow for large datasets, less interpretable.
Histogram of Oriented Gradients (HOG) + SVM	Extracts gradient features and uses SVM for classification.	Pedestrian detection, face recognition.	Robust to illumination changes, effective for object detection.	Sensitive to scale and viewpoint changes.
Principal Component Analysis (PCA)+ classifier	Reduces dimensionality before classification	Face recognition, image compression	Improves efficiency, removes noise.	Can lose important details in feature extraction.

Naive Bayes Classifier	Uses probability distributions to classify data based on prior knowledge.	Text recognition, document classification.	Computationally efficient, works well with small datasets	Assumes feature independence which is often unrealistic.

Verification from external references:

1. SZeilski, R computer vision: Algorithms and applications (2nd ed.) https://szeliski.org/Book/ Course literature.
2. https://medium.com/towards-data-science/pros-and-cons-of-various-classification-ml-algorithms-3b5bfb3c87d6
3. https://elitedatascience.com/machine-learning-algorithms

4.3 Segmentation

Using a 5D feature space (R,G,B,x,y) enhances segmentation by combining both color information and spatial location making sure that nearby pixels remain in the same region while preventing distant pixels of the same color from merging incorrectly. Unlike a purely color-based approach which may group similar colors regardless of their position. Adding spatial coordinates helps keep the objects edges and structure. This make the segmentation feel much more natural. This can be seen in the picture below where i implemented the mean-shift and used it on an image with balloons where multiple balloons have the same color to showcase how the segmentation is better with 5D feature space.

When changing the window size(bandwidth in my code) we get more details while higher values creates fewer segments, with larger regions.

Original Image

Segmented Image (Mean-Shift in 5D)