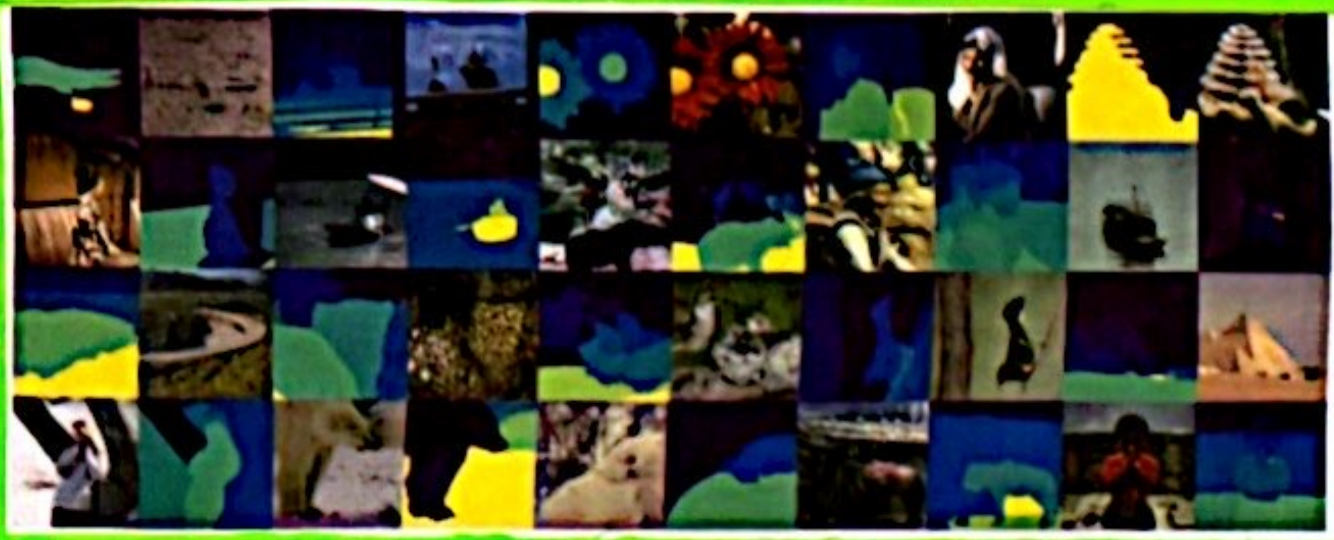
Introduction

- What we do - Focus on optimizing techniques for image segmentation, exploring innovative approaches to enhance segmentation performance. (Approach)
- What we aim - Identify the most effective approach for achieving high-quality segmentation results. (Goal)
- What we have - Segmenting images obtained from the *Berkeley Segmentation Dataset 500*. (Dataset)

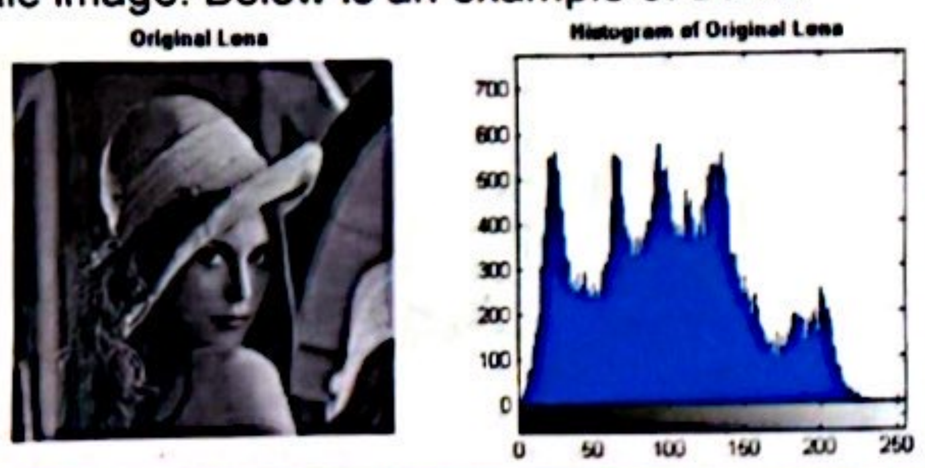


Methods

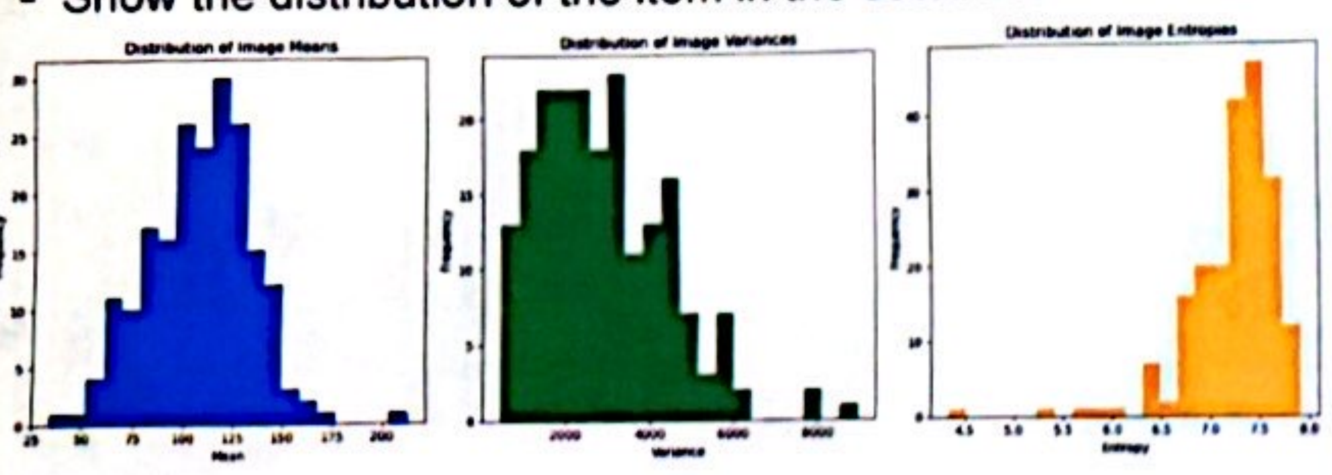
- Solution I - Threshold-based
  - Solver: Genetic Algorithm
  - Solver: 1st Order Gradient Descent
- Solution II - Similarity-based
  - Solver: Alternating Optimization
  - Solver: Genetic Algorithm (Search space too large for optimization)

Analysis

- Calculate and visualize the normalized histogram of a grayscale image. Below is an example of *Lena*:



- Show the distribution of the item in the database



Mean Variance Entropy

- Images with larger contrast usually achieve better segmentation quality (the right part of the variance and entropy maps).
- Run different segmentation methods

- **Threshold-based**

Define the objective function as:

$$J(\mathbf{T}) = \sum_{k=1}^{C} P_k(\mu_k - \mu)^2$$

P_k is the probability of the K-th class
μ_k is the mean intensity of the class
μ is the overall mean intensity

- Gradient descent optimization:

1) Compute the partial derivative of $J(\mathbf{T})$ with respect to T_k
2) Use gradient descent to optimize T_k, that is:

$$T_k \leftarrow T_k - \eta\frac{\partial(-J)}{\partial T_k} = T_k + \eta\frac{\partial J}{\partial T_k}$$

*The details of the derivation are discussed in more detail in the report.

- Genetic Algorithm:

Encodes threshold sets as chromosomes and optimizes the objective function J(T) by maximizing between-class variance through selection, crossover, and mutation operations

- **Similarity-based**

Define the objective function as:

$$J = \sum_{i=1}^{N}\sum_{k=1}^{K} z_{ik}(\alpha\|\mathbf{x}_i - \mu_k\|^2 + \beta\|(r_i, c_i) - \mathbf{p}_k\|^2)$$

$\mathbf{x}_i$: Pixel intensity;
μ_k: Cluster intensity center.
$\mathbf{p}_k$: Cluster spatial center.
(r_i, c_i): Pixel spatial coordinates;
α, β: Weights for intensity and spatial similarity.

- Alternating optimization:
  - Cluster Centers Update:

$$\mu_k = \frac{\sum_{i=1}^{N} z_{ik}\mathbf{x}_i}{\sum_{i=1}^{N} z_{ik}};\quad \mathbf{p}_k = \frac{\sum_{i=1}^{N} z_{ik}(r_i, c_i)}{\sum_{i=1}^{N} z_{ik}}$$

  - Cluster Assignments Update:

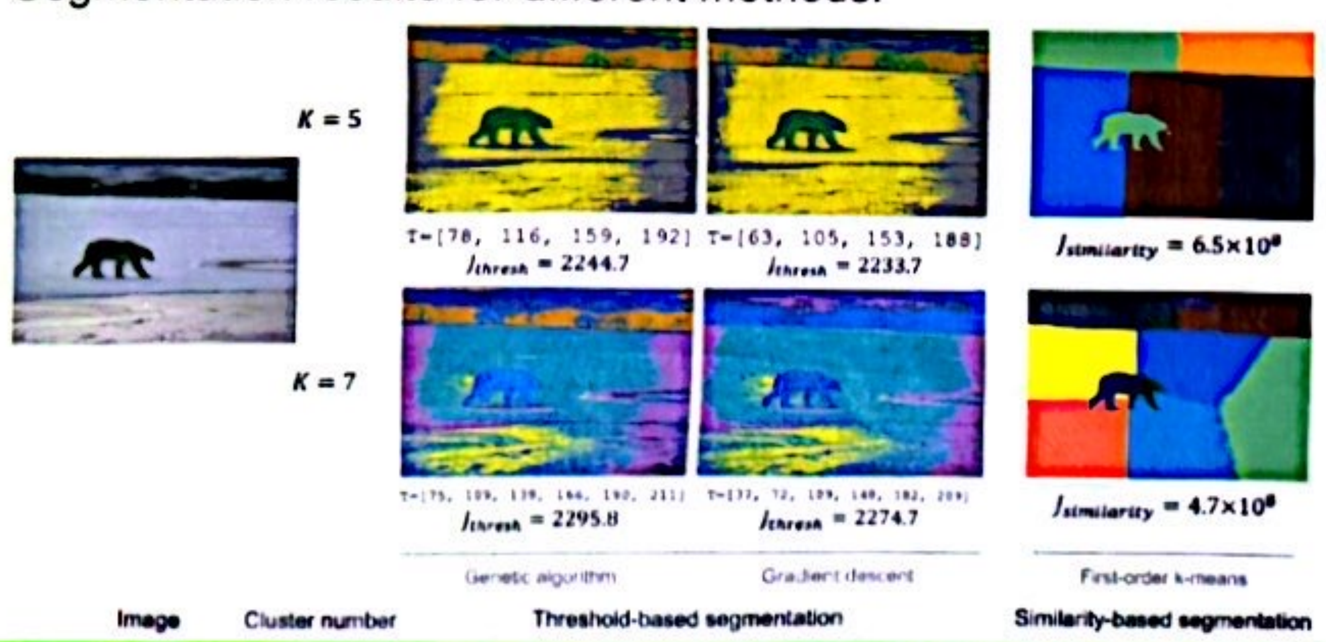
Assign pixels to clusters by minimizing the distance metric.

Results

Using J-value (split quality) and run time as the main evaluation:

- Gradient Descent:
  - Optimal in terms of running time;
  - May lead to local optimization.
- Genetic Algorithm:
  - Performs better in segmentation quality;
  - Takes a longer time to run.
- Similarity-Based:
  - Combining color and space information fits human perception;
  - Run time is limited by parameters and the speed of convergence.

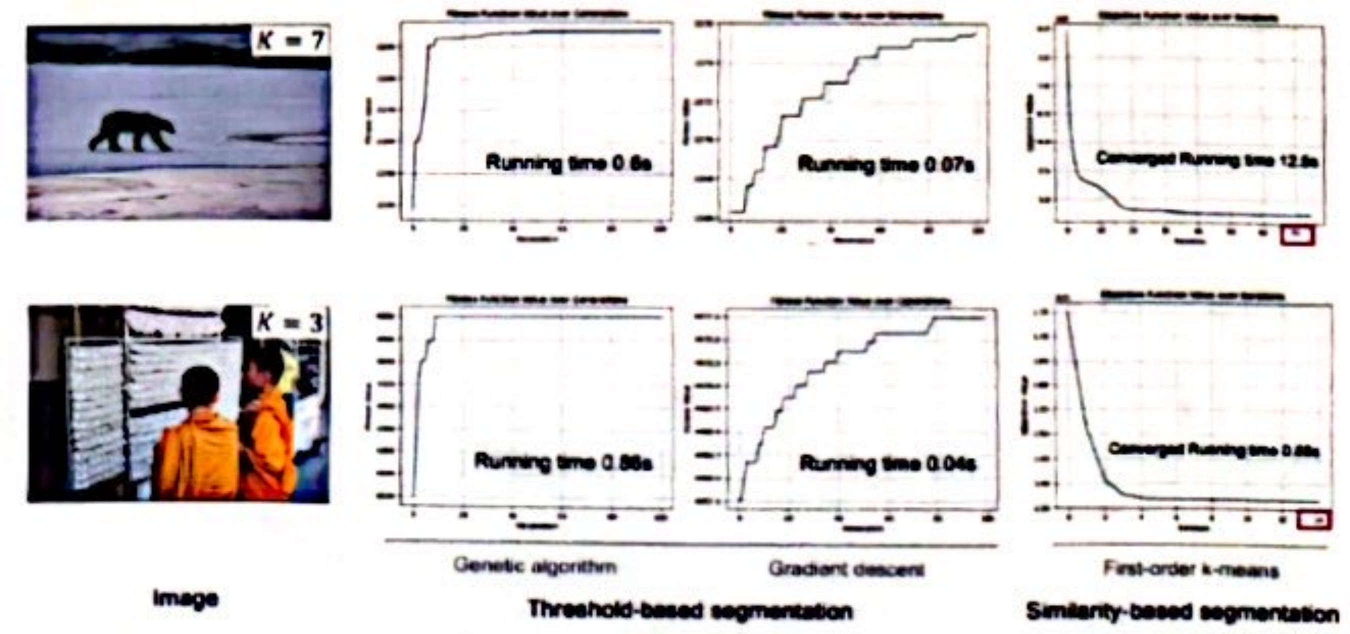
Segmentation results for different methods:

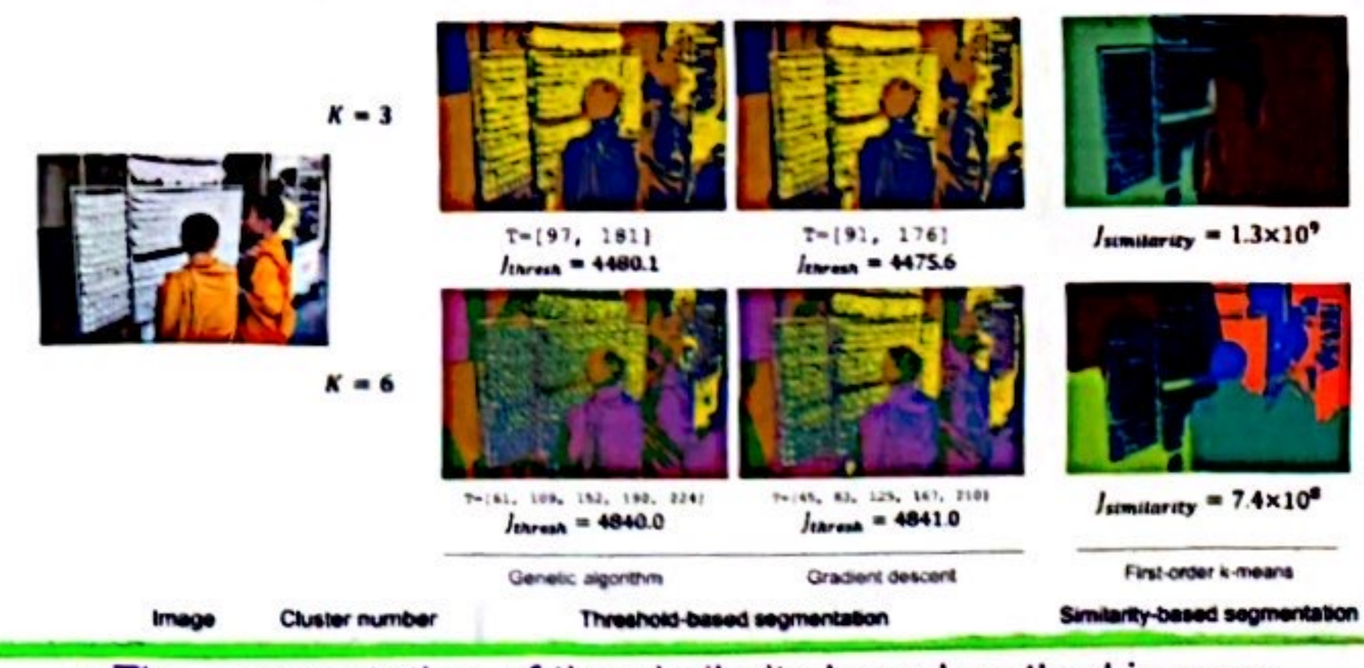


- The segmentation of the threshold-based method is more precise, but it is more likely to be over-segmentation.

- Challenge Analysis
  - Genetic algorithms require careful tuning of parameters. ex: population size and variability.
  - The Similarity-Based method is highly sensitive to α and β selection.
  - Notice the trade-off between *J-value* & *runtime*.
  - Balance between *simplicity* & *computational complexity*.

>>> Comparison





- The segmentation of the similarity-based method is more clustered and aligns better with perceptual logic.

Conclusion

- Performance Trade-offs:
  - Threshold-based methods achieve numerically better results with faster runtimes.
  - Similarity-based methods yield more cohesive segmentations, closer to human perception.
- Key Takeaways:
  - Each method has unique strengths and is suitable for specific scenarios.
  - Balancing accuracy and computational efficiency is crucial for practical applications.
- Future Applications:
  - Potential uses include medical imaging, autonomous driving, and land-use classification.

Reference

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