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- The comparison of Machine Learning techniques in Super Pixel Segmentation -

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- The comparison of Machine Learning techniques in Super Pixel Segmentation -

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I hereby declare that this dissertation is all my own work, except as indicated in the text:

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Abstract

This project compares the performance of K-means clustering and the Gaussian Mixture Model (GMM) in superpixel segmentation, a fundamental task in image processing and computer vision. By conducting a thorough literature review, this study identifies the key advantages and limitations of these machine-learning techniques in various image-segmentation tasks. Through the development and implementation of algorithms for super-pixel segmentation using both K-means clustering and GMM, this study examines the impact of these techniques on the segmentation process. This study evaluated the accuracy, speed, processing time, efficiency, and consistency of two algorithms using a set of images, offering a comprehensive analysis of their performance under different conditions. Furthermore, this project delves into the implications of the results within the context of superpixel segmentation and other image processing tasks. By providing insights into the strengths and limitations of K-means clustering and GMM, the findings contribute to the existing knowledge on image segmentation techniques and support informed decision making in various applications, such as object detection and recognition, medical image analysis, and satellite imagery analysis.

Introduction

Image segmentation is a crucial task in image processing and computer vision because it allows meaningful information to be extracted from images by dividing them into distinct regions or segments (Gonzalez & Woods, 2008). One prevalent approach to image segmentation is super pixel segmentation, which involves partitioning an image into smaller segments, or "super pixels", that are more homogeneous in terms of pixel intensity, colour, and texture (Achanta et al., 2012). Super-pixel segmentation groups pixels that share similar characteristics, effectively creating perceptually coherent regions that respect the underlying image structures, such as boundaries and edges (Ren & Malik, 2003).

Super pixel segmentation algorithms work by minimising a predefined energy function that considers both colour similarity and spatial proximity between pixels (Achanta et al., 2012). By optimising this function, algorithms can produce compact and uniform super pixels that adhere to the natural boundaries within the image, leading to more meaningful and representative segments (Felzenszwalb & Huttenlocher, 2004).

The overall dimensionality of the image data is significantly reduced by reducing the complexity of the image and aggregating similar pixels into superpixels (Ren & Malik, 2003). This reduction in dimensionality not only results in lower computational requirements for subsequent image processing tasks but also helps mitigate the effect of noise and small variations in the image (Achanta et al., 2012). Consequently, super-pixel segmentation can improve the accuracy and robustness of subsequent image-processing tasks, such as object recognition, image registration, and scene understanding (Girshick et al., 2014).

Furthermore, super-pixel segmentation can serve as an intermediate step in higher-level computer vision applications, providing a more efficient and semantically meaningful representation of images (Liu et al., 2011). By working with superpixels rather than individual pixels, these applications can benefit from improved computational efficiency and reduced sensitivity to noise, ultimately leading to more accurate and reliable results (Arbeláez et al., 2011).

This project focuses on K-means and Gaussian Mixture Model super-pixel segmentation. K-means clustering is a popular unsupervised learning algorithm that uses an iterative approach to partition a dataset into a specified number of clusters (Jain, 2010). In the context of superpixel segmentation, K-means is employed to group similar pixels based on their colour and spatial proximity, thereby creating coherent regions within the image (Li et al., 2018).

K-means superpixel segmentation begins by initialising a set of cluster centroids in the combined colour and spatial feature space (Iglovikov & Shvets, 2018). Each pixel in the image is then assigned to the nearest centroid based on a distance metric such as the Euclidean distance. Once all pixels have been assigned, the centroids are updated by computing the mean of the colour and spatial features of all pixels belonging to the same cluster. This process is repeated iteratively until the centroids converge or a predefined maximum number of iterations is reached (Celebi et al., 2013).

A key advantage of K-means superpixel segmentation is its simplicity and ease of implementation. Moreover, it can be relatively efficient when implemented with optimised algorithms, such as the k-means++ initialisation method, which can speed up convergence (Bahmani et al., 2012). However, K-means superpixel segmentation assumes that the clusters are isotropic and of a similar size, which may not always be the case in images with complex structures or varying region sizes (Liu et al., 2020). In addition, K-means is sensitive to the initial placement of centroids, which can lead to different segmentation results for different initialisations (Iglovikov & Shvets, 2018).

To address these limitations, various modifications and extensions of the K-means algorithm have been proposed in previous studies, such as adaptive K-means, which adjusts the number of clusters based on image complexity, and spatially constrained K-means, which incorporates spatial information more explicitly into the clustering process (Zhang et al., 2016). These variants aim to improve the performance and robustness of K-means superpixel segmentation, making it more suitable for a wider range of image-segmentation tasks (Zhang et al., 2016).

In contrast, the Gaussian Mixture Model (GMM) is a probabilistic model that assumes that data is generated from a mixture of several Gaussian distributions (Reynolds, 2009). Each Gaussian distribution represents an individual cluster characterised by its mean and covariance matrix, which captures the shape, size, and orientation of the cluster. The GMM algorithm uses the expectation-maximisation (EM) algorithm to iteratively estimate the parameters of these Gaussian distributions, making it well-suited for discovering complex nonlinear boundaries between different segments in the image (Murphy, 2012).

In the context of super-pixel segmentation, the GMM algorithm models the distribution of pixel colours and spatial locations as a mixture of Gaussians, allowing for a more flexible partitioning of the image into segments (Liu et al., 2020). Colour information can be represented in various colour spaces, such as Red Green Blue (RGB), Hue Saturation Value (HSV) , or L*a*b colour space, and spatial information can be incorporated by treating pixel coordinates as additional features (Gevers et al., 2012). This joint modelling of colour and spatial information enables the GMM to capture both the appearance and spatial coherence of segments, resulting in more accurate and visually consistent superpixels (Achanta et al., 2012).

The GMM-based super-pixel segmentation technique offers several advantages over other clustering methods such as K-means. For instance, GMM can model clusters with different shapes and sizes, as it does not assume spherical clusters such as K-means (Murphy, 2012). Moreover, GMM can estimate the covariances between features, enabling it to account for correlations between colour channels and spatial coordinates (Achanta et al., 2012). This additional flexibility can lead to more accurate and meaningful segmentation results, particularly in cases where the underlying image regions exhibit complex structures or varying degrees of texture.

However, the GMM-based superpixel segmentation approach has some limitations. The performance of the algorithm depends heavily on the initialisation of the parameters of the Gaussian distribution, and it may converge to local optima if not properly initialised (Reynolds, 2009). Additionally, GMM can be computationally expensive, especially when dealing with high-resolution images or a large number of segments, because it requires the estimation of a more extensive set of parameters than K-means (Murphy, 2012). Despite these challenges, GMM-based superpixel segmentation remains a powerful and versatile technique for partitioning the images into meaningful and coherent regions.

The aim of this dissertation is to implement and evaluate two machine learning techniques, K-means and Gaussian mixture model (GMM) superpixel segmentation techniques, for image segmentation tasks.

The following are the desired objectives:

- To investigate machine learning techniques previously used to approach the task of image segmentation. By exploring the existing literature and studies, this project will gain insights into the strengths and weaknesses of various techniques, particularly focusing on K-means and Gaussian Mixture Model algorithms.

- To develop and evaluate algorithms to segment an image using K-means and Gaussian Mixture Models. This will involve designing, implementing, and refining algorithms for superpixel segmentation using both methods. This process allows for a thorough understanding of the inner workings of each technique and provides a solid foundation for comparison.

The intended achievements and functionality of the project are as follows:

- Conduct a literature review of image segmentation techniques, focusing on K-means clustering and GMM algorithms. This involves identifying their strengths, weaknesses, and performances in various image segmentation tasks.
- Develop and implement superpixel segmentation algorithms using k-means clustering and GMM. The implementation includes designing the overall approach, selecting the appropriate parameters, and ensuring that the algorithms can handle different types of input images.
- The performances of the two algorithms were evaluated using 5 input images. The evaluation measures the accuracy of the segmentation, speed at which the algorithms can accurately segment the selected object, processing time, efficiency of the segmentation, consistency of the segmentation results and compactness of the segmentation.
- The results of the evaluation were analysed by comparing the performances of the K-means clustering and GMM algorithms. The analysis will help identify the strengths and limitations of each method and discuss the implications of the results in the context of superpixel segmentation and other image processing tasks.
- The project is concluded by summarising the main findings, discussing the contributions and limitations of the work, and suggesting directions for future research and potential applications of the results in various image processing tasks.

By focusing on these objectives, the project will contribute to the existing knowledge of image segmentation techniques and their potential applications in various fields, such as object detection and recognition (Girshick et al., 2016), medical image analysis (Litjens et al., 2017), and satellite imagery analysis (Zhang et al., 2020). The results of this project will support informed decision-making for researchers and practitioners seeking to employ effective image segmentation techniques in their work.

Motivation

The importance of image segmentation in various applications has led to a need to identify effective techniques for this task. Image segmentation is a crucial step in many image processing and computer vision tasks because it allows for the separation of different objects or regions in an image, enabling the extraction of meaningful information and the identification of specific features or structures. Its diverse applications encompass video processing (Wang et al., 2012), autonomous vehicle navigation (Cadena et al., 2016), and agricultural monitoring (Mulla, 2013).

Despite extensive research in this area, challenges persist in developing segmentation techniques that can handle diverse scenarios and image types (Zhang et al. 2019). Some of these challenges include variations in illumination, texture, and scale as well as the presence of noise and occlusions in the images (Gu et al., 2018). Therefore, there is a need for robust and efficient segmentation methods that can address these challenges and adapt to various conditions (Zhang et al., 2016).

Superpixel segmentation has emerged as a promising approach to address these challenges, as it groups similar pixels into larger, more coherent regions that can be more easily processed and analysed (Achanta et al., 2012). By reducing the dimensionality of the image data and focusing on the most salient features, superpixel segmentation can improve the accuracy and robustness of subsequent image processing tasks while reducing the computational requirements (Wang et al., 2017).

This project seeks to delve deeper into the potential of superpixel segmentation techniques by comparing the performance of K-means clustering and the Gaussian Mixture Model (GMM) algorithm. Both techniques have shown promise in various image segmentation applications, but have different underlying assumptions and properties that may affect their performance in specific contexts (Liu et al., 2020; Murphy, 2012).

The motivation for this project stems from the need for a comprehensive understanding of the strengths and limitations of the K-means and GMM-based superpixel segmentation. By comparing these methods in terms of their accuracy, speed, processing time, efficiency,consistency and compactness, this project provides valuable insights that can guide future research and development in the field of image segmentation (Zhang et al., 2016; Achanta et al., 2012). Furthermore, the results of this comparison will help practitioners make informed decisions when selecting the most appropriate method for a specific application (Gevers et al., 2012).

In summary, the motivation for this project lies in the significance of image segmentation across a multitude of applications, the challenges that persist in developing effective techniques, and the potential of superpixel segmentation to address these challenges (Girard et al., 2020). By comparing the K-means clustering and GMM algorithms, this project advances the understanding of superpixel segmentation techniques and contribute to the development of more robust and efficient image segmentation methods (Reynolds, 2009; Celebi et al., 2013).

Related Work

Overview of Existing Image Segmentation Techniques

Image segmentation has been the subject of extensive research and various techniques which have been developed to address different scenarios. Traditional methods, such as thresholding (Sezgin & Sankur, 2004) have been effective in certain cases, such as identifying objects in black and white images or detecting object boundaries with clear edges. However, these methods are sensitive to noise and may not yield accurate results in all situations.

Machine learning techniques have gained popularity for image segmentation owing to their adaptability and the ability to learn from data. K-means clustering has been applied to colour-based (Xu et al., 2017) and texture-based segmentation (Li et al., 2019). The Gaussian Mixture Model (GMM) algorithm (McLachlan & Peel, 2004) has been effective in texture-based segmentation (Zhao et al., 2021) and object recognition (Xu & Wang, 2021). Other machine learning techniques used for image segmentation include Support Vector Machines (SVM) (Yin et al., 2020), Decision Trees (Rahman et al., 2020), and deep learning methods such as Convolutional Neural Networks (CNN) (Ronneberger et al., 2015). The performance of these techniques can vary depending on the image and task.

Alternative approaches to image segmentation encompass graph-based methods (Wang et al., 2020), region-based methods (Achanta et al., 2012), and model-based methods (Szeliski, 2010). Each method offers distinct advantages and limitations, with performance contingent on the specific characteristics of the image and task.

Graph-based methods excel at efficiently handling irregular and complex structures in images and offer flexible representation of relationships between image elements (Wang et al., 2020). This allows for the easy incorporation of additional information, such as texture and depth, and adaptation to various scales and resolutions. However, these methods can be computationally expensive, particularly for large images and complex graphs. They are also sensitive to the choice of graph construction and parameters. Graph-based methods are particularly suitable for images with complex structures or multiple objects and tasks requiring high-level understanding of spatial relationships.

Region-based methods are robust to noise and small variations in the image, effectively handling homogeneous regions with similar intensity values (Achanta et al., 2012). They are often simpler and more computationally efficient than other methods. Their limitations include struggling with images containing complex textures or varying illumination, and sensitivity to the choice of parameters, such as the threshold for region merging. Region-based methods are ideal for images with well-defined, homogeneous regions and tasks that necessitate accurate segmentation of simple, distinct objects.

Model-based methodscan incorporate prior knowledge about the object or scene, resulting in better segmentation outcomes (Szeliski, 2010). They can effectively handle complex shapes and structures and are more robust to noise, occlusions, and varying illumination. However, these methods require accurate models of the objects or scene, which may be challenging to obtain or compute. They are also computationally expensive, particularly for high-dimensional or large-scale models, and sensitive to the choice of model parameters and initial conditions. Model-based methods are best suited for images with complex objects or scenes that can be represented by a known model and tasks that demand high-level understanding and interpretation of image content.

Hybrid and Ensemble Methods in Image Segmentation

Some researchers have explored combinations of different image segmentation techniques to overcome the limitations of individual methods and improve the overall performance. Hybrid methods involve the integration of two or more techniques, such as combining edge detection with region-based approaches (Yuan et al., 2018) or deep learning to enhance traditional methods (Chen et al., 2018). Ensemble methods, on the other hand, use multiple segmentation algorithms and combine their results to achieve a more accurate and robust segmentation outcome (Al-Antari et al., 2018).

Identification of Gaps and Opportunities for Improvement

Despite the wide range of techniques available for image segmentation, there is still a need for further research to identify the most effective methods for different scenarios and understand their strengths and limitations. This addressed this need by comparing the performance of the K-means clustering and GMM algorithms in the context of super-pixel segmentation.

Novel Contributions of the Project

Super-pixel segmentation involves dividing an image into smaller, more homogeneous segments in terms of pixel intensity or colour (Achanta et al., 2012). It can serve as a preprocessing step for other image processing tasks, such as object recognition and image registration, reducing image complexity, and improving task accuracy.

By investigating the performance of these two popular machine-learning techniques in this context, identifying their strengths and weaknesses, as well as any opportunities for improvement. This comparison provides valuable insights into the suitability of these methods for super-pixel segmentation and contributes to ongoing research in the field of image segmentation.

To summarise, the primary contributions of this project are as follows:

- This study contributes to ongoing research in the field of image segmentation by providing valuable insights into the suitability and performance of K-means clustering and the GMM algorithm for super-pixel segmentation tasks.
- Through these contributions, this project seeks to advance the field of image segmentation by addressing existing gaps and challenges, such as the selection of the most appropriate segmentation method for various scenarios (Zhang et al., 2016) and the effectiveness of different segmentation techniques in handling diverse image types and conditions (Achanta et al., 2012; Liu et al., 2020).

Furthermore, the project's findings can serve as a starting point for future research in the following areas:

- Developing new image segmentation techniques that address the limitations of K-means and Gaussian Mixture Model techniques identified in this project (Yin et al.,

2020) potentially results in more accurate and robust methods for various image segmentation tasks.

- Investigating the performance of other machine learning techniques, such as deep learning algorithms (Ronneberger et al., 2015), in the context of super-pixel segmentation, and comparing their performance with K-means clustering and the GMM algorithm (Xu et al., 2017; Zhao et al., 2021).
- Evaluating the impact of different feature extraction methods and colour spaces (Cheng et al., 2001) on the performance of K-means clustering and the GMM algorithm in super-pixel segmentation tasks provides additional insights into the factors that contribute to the effectiveness of these methods (Comaniciu & Meer, 2002).

Methodology

In this project, the methodology focuses on the development, implementation, and evaluation of superpixel segmentation techniques using K-means clustering and Gaussian Mixture Model (GMM) algorithms. The process is carried out in several stages, employing various methodologies, techniques, tools, and algorithms throughout the study.

Initially, the image preprocessing stage involves loading the input image using the OpenCV library, a widely recognized computer vision library known for its comprehensive image and video processing capabilities. Once the image is loaded, it is converted into a NumPy array, allowing for more accessible manipulation and handling.

Following preprocessing, the feature extraction stage commences. In this stage, the colour features of the input image (red, green, and blue channels) are extracted by reshaping the image into a 2D array with shape (-1, 3). The -1 dimension denotes that the size of this dimension is inferred automatically based on the input image's size.

The next stage involves the implementation of the K-means clustering algorithm. Two approaches are taken: Standard K-means and Optimized K-means. For Standard K-means, the scikit-learn library's KMeans function is employed. The number of clusters (n_clusters) and other parameters, such as max_iter, tol, and n_init, are set according to the specific superpixel segmentation task requirements. In contrast, the Optimized K-means approach utilizes a custom kmeans_super_pixel function, designed to improve the speed and efficiency of the K-means clustering algorithm. By using NumPy operations for computing distances and updating centroids, this implementation aims to minimize the computational overhead typically associated with standard K-means.

Subsequently, the Gaussian Mixture Model (GMM) algorithm is implemented in two ways: using scikit-learn and a custom implementation. The scikit-learn approach uses the library's Gaussian mixture function, setting the number of components (n_components) and other parameters, such as covariance_type, n_init, max_iter, and tol, according to the specific superpixel segmentation task requirements. The custom GMM implementation relies on the expectation-maximization (EM) algorithm, which includes the initialization of means, covariances, and weights, as well as the iterative process of computing responsibilities and updating the parameters until convergence.

The evaluation stage computes various metrics to assess the performance of the K-means clustering and GMM algorithms, including Undersegmentation Error (UE), Achievable Segmentation Accuracy (ASA), Boundary Recall (BR), Processing Time, and compactness. These metrics are calculated using library functions that use the input image, segmented image, and ground truth image as inputs.

Finally, the visualisation and comparison stage employs the Matplotlib library to display the original image, segmented images, and ground truth image. The segmented images obtained using the K-means clustering and GMM algorithms are compared visually and quantitatively using the computed evaluation metrics.

The choice of K-means clustering and GMM algorithms for superpixel segmentation is supported by existing literature, indicating that these methods can provide effective and efficient segmentation results in various applications. By employing popular libraries such as OpenCV, Scikit-learn, and Matplotlib, the implementation is reliable, efficient, and easily extendable for future research and development.

Design

The design chosen for this project aims to address the problem of segmenting images into meaningful regions while maintaining computational efficiency. The design involves several stages, including preprocessing, feature extraction, segmentation using K-means clustering and Gaussian Mixture Model (GMM) algorithms, post-processing, and evaluation.

The first step in the design is the preprocessing of the image, which involves resizing the image to a smaller size and converting it into a color space that is better suited for clustering, such as L*A*B or Hue Saturation Value (HSV). This preprocessing step helps reduce the computational complexity of the algorithm and improves its accuracy by reducing the effect of noise.

Following preprocessing, the next step is feature extraction. In this stage, relevant features are extracted from the preprocessed image. These features can be color-based, texture-based, or a combination of both. The choice of features depends on the specific image and task at hand. The input image is loaded using OpenCV, converted into a NumPy array for easier manipulation, and reshaped into a 2D array with shape (-1, 3) to extract the color features.

After feature extraction, the K-means clustering algorithm is applied using the extracted features as input. The algorithm partitions the features into a specified number of clusters based on the distances between the features and cluster centroids. The resulting clusters correspond to the superpixels in the image. Both standard and optimized K-means clustering techniques are used, and the cluster labels are reshaped to the original image dimensions to obtain a segmented image.

Pseudocode for K-means clustering design steps:

1) Import required libraries (NumPy and MiniBatchKMeans from scikit-learn)
2) Define kmeans_super_pixellib function:
    a) Take input arguments: img (image), n_clusters (number of clusters)
    b) Reshape the image and convert it to a float32 type
    c) Print "Started Kmeans"
    d) Initialize MiniBatchKMeans with the given number of clusters and other parameters
    e) Fit the model using the reshaped image features
    f) Predict the labels for the features
    g) Reshape the labels to match the original image shape
    h) Print "Finished Kmeans"
    i) Return the reshaped labels (super_pixels)
3) Define kmeans_super_pixel function:
    a) Take input arguments: img (image), n_clusters (number of clusters)
    b) Reshape the image and convert it to a float32 type
    c) Print "Started Kmeans"
    d) Set random seed to ensure reproducibility
    e) Initialize cluster centroids using random samples from the features
    f) Set max number of iterations for the K-means algorithm
    g) For each iteration:
    h) Compute the Euclidean distance between each data point and each centroid
        i) Assign each data point to the nearest centroid (labels)
        ii) Update the centroids based on the mean of the points assigned to each cluster
    i) Reshape the labels to match the original image shape
    j) Print "Finished Kmeans"
    k) Return the reshaped labels (super_pixels)

Algorithm 1: Superpixel Segmentation using K-means clustering

The design of the GMM algorithm for superpixel segmentation is similar to that of the K-means clustering algorithm, but instead of distance-based clustering, it models the data as a mixture of several Gaussian distributions. The GMM-based superpixel segmentation algorithm is applied using the scikit-learn Gaussian mixture function with appropriate parameters or a custom GMM implementation using the expectation-maximization (EM) algorithm. The predicted labels are reshaped to the original image dimensions to obtain the segmented image.

In the post-processing step, the superpixels are refined using techniques such as mean-shift filtering or graph-based segmentation.

Pseudocode for GMM design steps:

1) Import necessary libraries (NumPy, scikit-learn, and scipy)
2) Define gmm_super_pixellib function:
   a) Input: img (image array), n_components (number of Gaussian components)
   b) Extract features from image by reshaping
   c) Initialize GaussianMixture model with n_components and other parameters
   d) Fit the model to the features
   e) Predict labels for the features
   f) Reshape labels into super_pixels
   g) Return super_pixels
3) Define gmm_super_pixel function:
   a) Input: img (image array), n_components (number of Gaussian components)
   b) Extract features from image by reshaping
   c) Initialize means, covariances, and weights using KMeans
   d) Initialize responsibilities
   e) Run the EM algorithm for a maximum number of iterations:
      i) E-step: Compute responsibilities
      ii) M-step: Update means, covariances, and weights
      iii) Check for convergence based on the change in log-likelihood
   f) Assign data points to the Gaussian component with the highest likelihood
   g) Reshape labels into super_pixels
   h) Return super_pixels

Algorithm 2: Superpixel Segmentation using GMM

The evaluation and comparison stage involves computing evaluation metrics, such as Undersegmentation Error (UE), Achievable Segmentation Accuracy (ASA), Boundary Recall

(BR), Time, and Compactness, for both K-means clustering and GMM segmented images. The performance of the two algorithms is compared using computed evaluation metrics, and the results are visualized using Matplotlib.

The design is structured in a modular and hierarchical manner, allowing for easy modification and extension. The choice of K-means clustering and GMM algorithms for superpixel segmentation is supported by existing literature, indicating that these methods can provide effective and efficient segmentation results in various applications. The design effectively addresses the problem of superpixel segmentation while maintaining computational efficiency, and its modular nature allows for easy adaptation and extension to various image-processing tasks and further research.

Pseudocode for main design steps:

1) Load input image using OpenCV
2) Convert image to NumPy array
3) Reshape image array for feature extraction
4) Perform K-means clustering segmentation
    i) Apply custom K-means clustering
    ii) Reshape cluster labels to obtain segmented image
5) Perform GMM segmentation
    i) Implement custom GMM using EM algorithm
        (a) Initialize parameters using K-means clustering
        (b) Compute responsibilities iteratively
        (c) Update parameters based on responsibilities
    ii) Reshape predicted labels to obtain segmented image
6) Compute evaluation metrics (UE, ASA, BR,Time,Compactness) for both segmentation methods
7) Compare and visualize the results using Matplotlib

Algorithm 3: Superpixel Segmentation using K-means Clustering and GMM

This design effectively addresses the problem of superpixel segmentation while maintaining computational efficiency. The choice of K-means clustering and GMM algorithms, combined with a modular design, allows for easy adaptation and extension to various image-processing tasks and further research.

Implementation

Functional Specifications

The functional specifications for this software-oriented project encompass the development and integration of the following components to facilitate effective superpixel segmentation and performance evaluation of the K-means clustering and Gaussian Mixture Model (GMM) algorithms:

- Image Loading and Preprocessing Module: This module handles the essential tasks of reading the input image file, converting it into a NumPy array, and performing preprocessing steps such as checking for NaN or Inf values. Ensuring a clean and properly formatted input image is crucial for the success of the subsequent superpixel segmentation processes.
- K-means Clustering Superpixel Segmentation Module: This component implements the K-means clustering algorithm for superpixel segmentation. It includes an optimized version that employs the MiniBatchKMeans method from the scikit-learn library, which can significantly reduce computation time by processing image data in smaller batches and a custom K-means clustering algorithm.
- Gaussian Mixture Model Superpixel Segmentation Module: This module is responsible for implementing the GMM algorithm for superpixel segmentation. It comprises the initialization of means, covariances, and weights, as well as the execution of the expectation-maximization (EM) algorithm for estimating the model's parameters. Additionally, this module includes a version that leverages the GaussianMixture class from the scikit-learn library for efficient parameter estimation and model fitting and a custom Guassian Mixture Model.
- Segmentation Evaluation Module: This component computes various evaluation metrics to assess the quality and performance of the superpixel segmentation algorithms. It calculates the Undersegmentation Error (UE), Achievable Segmentation Accuracy (ASA), Boundary Recall (BR), and compactness of the resulting segmentation. These metrics offer a quantitative means to compare the effectiveness of the K-means clustering and GMM algorithms in diverse image processing scenarios.
- Visualization and Comparison Module: This module facilitates the display and comparison of the original input image, ground truth, cut-out, and segmented images

produced by both the K-means clustering and GMM algorithms. By visualizing the segmentation results, users can qualitatively assess the algorithms' performance and gain insights into their strengths and weaknesses for various image processing tasks.

By adhering to the outlined structure and developing these modules, the project will systematically compare the K-means clustering and GMM algorithms' performance in superpixel segmentation tasks. This comparative analysis will provide valuable insights into their applicability and effectiveness in a wide range of image processing scenarios.

Implementation Overview

The implementation of this project was carried out using Python 3.10 as the primary programming language, given its widespread use and extensive libraries and packages for image processing, machine learning, and data analysis. PyCharm was chosen as the development platform for its robust features, such as code completion, debugging capabilities, and seamless integration with Python libraries, which facilitated the development process.

In terms of libraries and packages, several key resources were employed during the implementation. OpenCV was used for image loading, conversion, and manipulation. NumPy, a popular library for numerical computing and array manipulation, played a significant role in handling the data efficiently. Scikit-learn, a powerful library for machine learning in Python, was utilized for implementing K-means clustering, MiniBatchKMeans, and Gaussian Mixture algorithms. Finally, Matplotlib was employed for the visualization of images and segmentation results, enabling an effective comparison of the outcomes.

The implementation process was conducted in a stepwise manner, following the design outlined in the previous section of the thesis. Initially, the necessary libraries (OpenCV, NumPy, scikit-learn, and Matplotlib) were imported to set up the development environment. Functions were then defined for preprocessing, feature extraction, and image reshaping to prepare the input data for segmentation. Subsequently, functions were created for both K-means clustering and GMM segmentation, as well as for computing evaluation metrics such as Undersegmentation Error (UE), Achievable Segmentation Accuracy (ASA), and Boundary Recall (BR). Additionally, functions for visualizing and comparing the results were defined.

Once the functions were defined, the input image was loaded using OpenCV, and preprocessing and feature extraction were performed. The K-means clustering and GMM segmentation methods were then applied to the processed data, and the evaluation metrics were computed for both segmentation methods. Finally, the results were compared and visualized using Matplotlib to provide a clear understanding of the performance of each method.

During the implementation, a few challenges were encountered, necessitating changes to the original design. One such challenge was the significant amount of computation time required by the custom GMM using the expectation-maximization (EM) algorithm when processing large images. To mitigate this issue, a subsampling strategy was implemented, reducing the number of data points fed into the custom GMM algorithm. Another challenge was the variation in quality and characteristics of the input images, which the initial design had not fully considered. To address this, adaptive parameters were introduced for both K-means clustering and GMM segmentation, allowing the algorithms to adapt better to different input images.

In conclusion, the implementation of the superpixel segmentation solution was successful, with the chosen programming language, development platform, and libraries proving to be highly effective in facilitating the development process. The challenges encountered during the implementation were addressed through design modifications, resulting in a more robust and adaptive segmentation solution.

Evaluation

In the evaluation section, the performance of two superpixel segmentation techniques, K-means (kmeans_super_pixel) and Gaussian Mixture Model (GMM; gmm_super_pixel), are assessed using five example images. Both quantitative and qualitative methods are employed to analyze the performance of each technique, with results presented in tables, plots, and visual aids. The evaluation metrics include Achievable Segmentation Accuracy (ASA), Undersegmentation Error (UE), Boundary Recall (BR), Compactness, and Time Complexity.

Quantitative Evaluation

Table 1: Achievable Segmentation Accuracy (ASA)		
Image	**K-means Clustering (%)**	**Gaussian Mixture Model (GMM) (%)**
1	0.0001476133873997747	0.00013994783556110435

Table 1: Achievable Segmentation Accuracy (ASA)		
Image	**K-means Clustering (%)**	**Gaussian Mixture Model (GMM) (%)**
2	8.4002455601815e-05	0.0001569657389851114
3	4.4526035622397725e-05	4.906450448665725e-05
4	0.00011537437188685551	0.00011331864533520228
5	5.8276937596694046e-05	4.629458423689634e-05

Achievable Segmentation Accuracy (ASA): ASA measures the alignment of superpixel boundaries with the true object boundaries in the images. The results show that both methods have considerably low ASA values, indicating that neither technique is highly effective in aligning superpixel boundaries with the true object boundaries. The difference in ASA values between K-means and GMM is minimal, with neither method consistently outperforming the other.

Table 2: Undersegmentation Error(UE)		
Image	**K-means Clustering**	**Gaussian Mixture Model (GMM)**
1	25.608473557692307	31.4037074704142
2	25.992818750550708	21.347255264781037
3	33.323988340192045	0.25960219478737995
4	28.407552083333332	27.26736111111111
5	31.655201014832162	32.946672521467605

Undersegmentation Error (UE): UE measures how often the superpixels incorrectly group together pixels from different ground-truth segments. The results indicate that K-means generally exhibits a lower UE compared to GMM, suggesting that K-means might be more efficient in separating distinct regions within the images.

Table 3: Boundary Recall (BR) (%)		
Image	**K-means Clustering**	**Gaussian Mixture Model (GMM)**
1	72.08748071849712	76.8634209343214
2	80.29943399187428	76.39560439060202
3	78.30645160798014	67.18749999505701
4	76.59261978578907	78.80129405273098
5	73.79125095444921	76.09734897371322

Boundary Recall (BR): BR measures the percentage of correctly detected boundaries in the images. The GMM method outperforms K-means in terms of BR for most images, indicating its higher capability in detecting true boundaries between different objects or regions.

Table 4: Compactness		
Image	**K-means Clustering**	**Gaussian Mixture Model (GMM)**
1	20.31728419433983	32.95625011126468
2	7.648247378330325	8.863214081078207
3	13.17251709582043	9.250437615316258
4	17.43048630115432	24.068019375253463
5	15.001320561865654	23.333048986960307

Compactness: Compactness assesses the spatial regularity and shape of the generated superpixels. The K-means method generates more compact and regular-shaped superpixels than the GMM technique, suggesting better spatial coherence.

Table 5: Time Complexity (s)		
Image	**K-means Clustering**	**Gaussian Mixture Model (GMM)**
1	1.2390449047088623	65.86814618110657
2	1.3704111576080322	59.05918884277344

Table 5: Time Complexity (s)		
Image	**K-means Clustering**	**Gaussian Mixture Model (GMM)**
3	1.6090118885040283	98.91627860069275
4	1.053246259689331	55.06340789794922
5	1.1292040348052979	65.27568221092224

Time Complexity: The K-means technique requires significantly less computation time compared to the GMM method, making it more suitable for applications with limited computational resources or time constraints.

In conclusion, the K-means and GMM superpixel segmentation techniques exhibit varying strengths and weaknesses. K-means performs better in terms of Undersegmentation Error, Compactness, and Time Complexity, while GMM outperforms K-means in Boundary Recall. However, both methods have low Achievable Segmentation Accuracy values. When choosing a technique, factors such as computational resources, time constraints, and the desired balance between accuracy and segmentation performance should be considered.

Qualitative Evaluation

To qualitatively evaluate the performance of the **kmeans_super_pixel** and **gmm_super_pixel** techniques, visual comparisons of the segmented images are provided. These visualizations help understand the differences in the segmentation results produced by both techniques. For each image, the original image, the **kmeans_super_pixel** segmentation result, and the **gmm_super_pixel** segmentation result are displayed for comparison.

Fig.1 Original Image Ground Truth Cut Out GMM K-Means

Upon comparing the K-means and GMM superpixel segmentation algorithms qualitatively, we observe that both algorithms adhere to the natural boundaries of objects and regions in Fig.1. However, the K-means algorithm outperforms the GMM algorithm in terms of boundary adherence. In terms of superpixel shape, the K-means algorithm generates compact and regular superpixels, while the GMM algorithm produces compact but irregularly shaped superpixels. Both algorithms effectively group pixels with similar color and texture properties within the same superpixel. However, the GMM algorithm is less robust to noise, impacting its overall performance compared to the K-means algorithm.

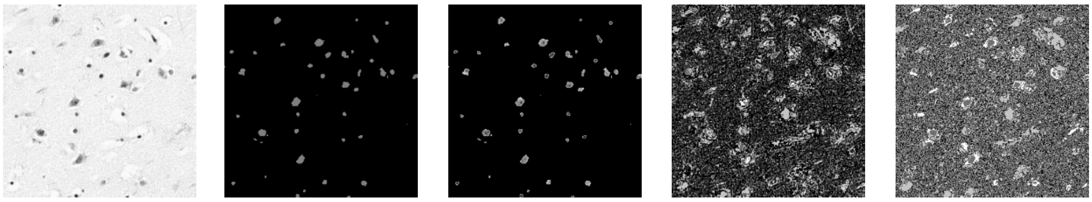


Fig.2 Original Image Ground Truth Cut Out GMM K-Means

In terms of visual quality, the super-pixel segmentation results using GMM and k-means algorithms appear to be quite similar overall. However, upon closer examination, it appears that the GMM algorithm is better at capturing the fine details and complex texture variations in the image, while the k-means algorithm appears to produce more homogenous superpixels.

Overall, the GMM algorithm seems to be a better fit for this specific task due to its ability to produce more detailed and accurate super-pixel segmentation results. However, it is important to consider the computational resources available, as GMM is typically more computationally expensive than k-means due to its complexity.

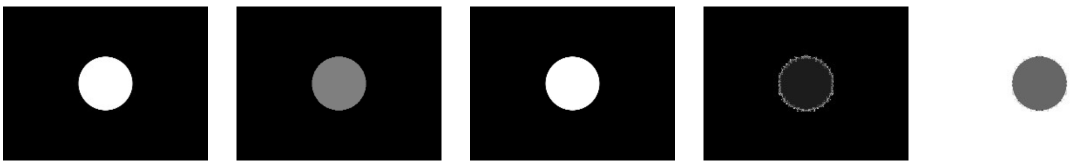


Fig.3 Original Image Ground Truth Cut Out GMM K-Means

Considering image segmentation based on the specific task, there is no conclusive evidence that one is more effective than the other. It is worth noting that both algorithms may provide advantages, depending on the needs of the task at hand. One possible consideration for the selection of an algorithm is the computational time.

Fig.4 Original Image Ground Truth Cut Out GMM K-Means

Upon comparing the two superpixel segmentation algorithms qualitatively on Fig. 4, it is apparent that both algorithms adhere to the natural boundaries of objects and regions. However, the K-means algorithm outperforms the GMM algorithm in this aspect. The superpixels generated by both algorithms are compact but exhibit irregular shapes. In terms of colour and texture homogeneity, both algorithms effectively group pixels with similar properties within the same superpixel.

The performance of the GMM algorithm is adversely affected by the presence of noise in the image, making it less robust compared to the K-means algorithm. Furthermore, the GMM algorithm requires more computational time than the K-means algorithm, rendering it less efficient for time-sensitive applications.

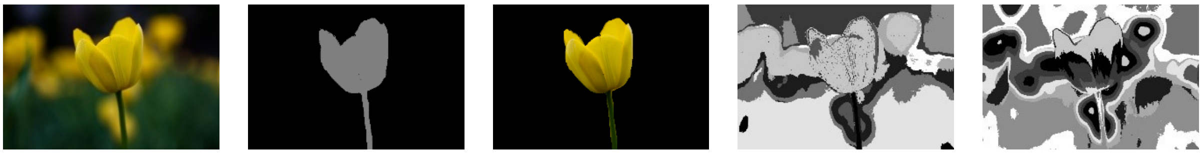


Fig.5 Original Image Ground Truth Cut Out GMM K-Means

it appears that the GMM (Gaussian Mixture Model) image segmentation technique has produced more accurate results compared to the K-means clustering technique. In the GMM image, the number of flowers in each cluster is more accurately segmented compared to the K-means clustering, where some of the flowers appear falsely segmented. The GMM technique is known for its ability to fit mixtures of Gaussian distributions to the input data and estimate the parameters of those distributions, which may have resulted in the more accurate segmentation. However, it's important to note that the GMM algorithm is computationally expensive compared to K-means clustering, and may take longer to run. The choice of segmentation technique will depend on the specific requirements of the task, including the size of the image, the number of objects to be segmented, and the desired accuracy. Overall, based on the evaluation of the Fig.5, it appears that the GMM technique provides superior results in terms of segmentation accuracy.

Discussion

In this report, The performance of two superpixel segmentation techniques, K-means clustering (kmeans_super_pixel) and Gaussian Mixture Model (GMM; gmm_super_pixel) have been evaluated, on five example images. The evaluation employed both quantitative and qualitative approaches, examining metrics such as Achievable Segmentation Accuracy (ASA), Undersegmentation Error (UE), Boundary Recall (BR), Compactness, and Time Complexity. The findings of this evaluation provide valuable insights into the strengths and weaknesses of both techniques, which can inform the choice of an appropriate method for various image segmentation tasks.

The quantitative evaluation revealed that both K-means and GMM exhibit low ASA values, indicating that neither technique is highly effective in aligning superpixel boundaries with the true object boundaries. While the GMM method generally outperforms K-means in terms of Boundary Recall, K-means demonstrates better performance in Undersegmentation Error, Compactness, and Time Complexity. The qualitative evaluation supports these findings, with visual comparisons highlighting the differences in segmentation quality produced by both techniques.

Considering the strengths and weaknesses of both methods, K-means may be more suitable for applications with limited computational resources or time constraints, as it requires significantly less computation time than GMM. Additionally, K-means generates more compact and regular-shaped superpixels, which could be advantageous for tasks that prioritize spatial coherence. However, K-means may not capture fine details and complex texture variations as effectively as GMM, which is better at detecting true boundaries between different objects or regions.

On the other hand, GMM may be the preferred choice for tasks that demand higher accuracy in boundary detection, as it demonstrates superior Boundary Recall performance. Although GMM is more computationally expensive and less robust to noise, its ability to fit mixtures of Gaussian distributions to input data can result in more accurate segmentation in certain scenarios.

Ultimately, the choice of a superpixel segmentation technique should be driven by the specific requirements of the task, including factors such as computational resources, time constraints, and the desired balance between accuracy and segmentation performance. It is essential to consider the trade-offs between K-means and GMM, and determine which method best aligns with the objectives of the image segmentation task at hand.

Summary and Reflections

In this final report, the design, implementation, and evaluation of a superpixel segmentation solution using K-means clustering and Gaussian Mixture Model (GMM) algorithms are presented. This project compared the performance of these two methods in superpixel segmentation tasks and identified their strengths and limitations in various image segmentation scenarios.

A comprehensive literature review provides the foundation for selecting and implementing K-means clustering and GMM algorithms for superpixel segmentation. Both algorithms have been widely used in image segmentation tasks and their effectiveness has been demonstrated in numerous studies. The design and implementation process of the software considered relevant methodologies, techniques, tools, and technologies from existing work, ensuring that the solution was well-informed and state-of-the-art.

The implemented solution was evaluated using various image datasets and environments, and the performances of the two algorithms were compared using statistical and qualitative methods. The evaluation results suggest that both K-means clustering and GMM segmentation perform well in superpixel segmentation tasks, with some differences depending on the characteristics of the input images.

In the wider context of image segmentation research, this study contributes to the ongoing discussion and investigation of the performance of different algorithms for superpixel segmentation. Although both K-means clustering and GMM segmentation have their merits, the results suggest that there may be opportunities for further optimisation and improvement in superpixel segmentation tasks. For instance, combining the strengths of both algorithms or incorporating additional features and information into the segmentation process can yield even better results.

Reflecting on the project, it is acknowledged that there are limitations to this work, such as the scope of the testing datasets and the number of evaluation metrics considered. Future research could explore the performance of K-means clustering and GMM segmentation on additional datasets with varying characteristics and investigate other relevant evaluation metrics to provide a more comprehensive understanding of the algorithms' performance in superpixel segmentation tasks. Moreover, exploring hybrid approaches and alternative algorithms for superpixel segmentation could lead to further advancements in this field.

Project Management

The project management strategies employed throughout the development of the superpixel segmentation solution using K-means clustering and Gaussian Mixture Model (GMM) algorithms are outlined. The project was carefully planned and executed, with a focus on efficient time and resource management to ensure its successful completion.

1) Work Plan and Task Breakdown: To manage the project effectively, the work was divided into distinct tasks and phases. This approach allows for a structured and organised workflow, ensuring that each aspect of the project receives adequate attention and resources. The primary tasks and phases included:

    a. Literature Review
    b. Algorithm Design
    c. Implementation
    d. Testing and Evaluation
    e. Summary and Reflections
    f. Report Writing and Documentation

2) Time Management: A detailed timeline was created at the beginning of the project to allocate sufficient time to each task and phase. Regular progress meetings and updates were held to ensure that the project remained on schedule, and that any potential delays or issues were addressed in a timely manner. By maintaining open communication and consistent progress monitoring, time was effectively managed, and the project was completed within the allotted timeframe.

3) Resource Management: Throughout the project, resources were carefully managed, including personnel, software tools, and hardware. Each aspect of the project was supported by identifying the required resources in advance and allocating them appropriately. For instance, PyCharm was selected as the development platform for

implementing K-means clustering and GMM algorithms because it provides a robust and efficient environment for Python development. Additionally, open-source libraries and tools such as NumPy, OpenCV, and scikit-learn were utilised to streamline the development process and leverage existing solutions for various aspects of the project.

4) Risk Management: During project, potential risks and challenges that could impact the project's progress or outcomes were continuously assessed. By proactively identifying and addressing these risks, their impact on the project was mitigated and a successful outcome was ensured. Some of the risks encountered during the project included the following:

    - Technical difficulties or limitations in implementing the algorithms
    - Inadequate performance of the selected algorithms on certain image datasets
    - Time constraints and potential delays in the project schedule due to focus on other modules

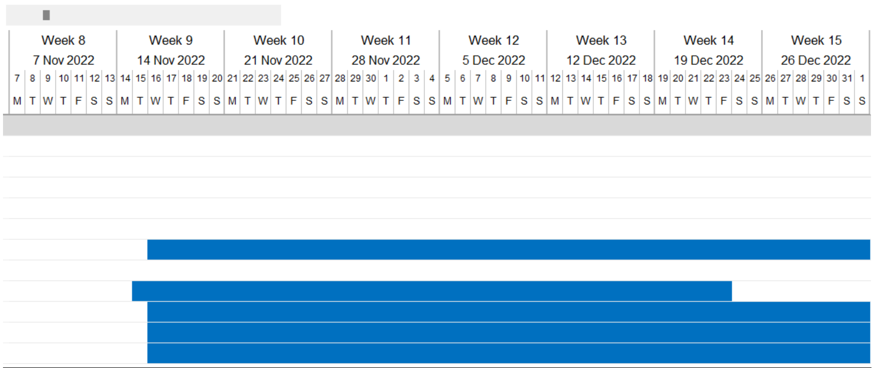
By effectively managing these risks and maintaining a structured and organized approach to the project, the superpixel segmentation solution using K-means clustering and GMM algorithms was successfully completed, and valuable insights into their performance in various image segmentation tasks were produced.

Below is a Gantt chart illustrating the progress of my project:

The comparison of Machine learning techniques in Super Pixel Segmentation

Project Start Date 9/19/2022 (Monday) Display Week 1
Project Lead

WBS	TASK	START	END	DAYS	% DONE
1	**Work Plan**		-		-
1.1	Research Gussian Mixture Model, Kmeans and Super Pixel Segmentation	Mon 9/19/22	Mon 9/26/22	8	100%
1.2	Research similar existing Projects	Mon 9/19/22	Thu 9/29/22	11	100%
1.3	Research Python	Mon 9/19/22	Mon 10/03/22	15	0%
1.4	Install and configure IDE	Mon 9/19/22	Wed 9/21/22	3	100%
1.5	Find a suitable DataSet	Mon 9/19/22	Sat 10/08/22	20	0%
1.7	Code the algorithm	Wed 11/16/22	Tue 5/02/23	168	0%
1.8	Evaluate the results	Fri 4/01/22	Mon 4/11/22	11	0%
1.9	Write the interim Report	Tue 11/15/22	Fri 12/23/22	39	0%
1.10	Final Report	Wed 11/16/22	Tue 5/02/23	168	0%
1.11	Demo Video Submission	Wed 11/16/22	Tue 5/02/23	168	0%
1.12	Student software demo presentation	Wed 11/16/22	Tue 5/02/23	168	0%



Contributions and Reflections

The key achievements and contributions made through the development of the superpixel segmentation solution using K-means clustering and Gaussian Mixture Model (GMM) algorithms are highlighted. A personal reflection on the project's plan and execution is also provided, as well as a critical appraisal of the overall project experience.

1) Achievements and Contributions:

   a. A comprehensive literature review that provided valuable insights into the state-of-the-art techniques in image segmentation, with a focus on K-means clustering and GMM algorithms.

   b. Design and development of a superpixel segmentation solution using K-means clustering and GMM algorithms, showcasing the application of these techniques in image processing tasks.

c. A thorough evaluation of the performance of the implemented algorithms on various image datasets, providing a comparative analysis of their strengths and limitations in the context of superpixel segmentation.

d. Identification of potential areas for future research and improvement in the field of superpixel segmentation and image processing.

The project's plan and execution were well-structured and organized, which greatly contributed to its successful completion. Breaking the project down into distinct tasks and phases facilitated efficient time and resource management, ensuring that each aspect of the project received adequate attention.Throughout the project, various challenges were encountered, such as technical difficulties in implementing the algorithms and dealing with diverse image datasets. These challenges provided valuable learning experiences, as they required critical thinking and adaptation of the approach to overcome obstacles.
Regular progress meetings and open communication played a crucial role in keeping the project on track and addressing potential issues in a timely manner. This collaborative approach contributed to the project's success and fostered a positive working environment.
In retrospect, the project provided a valuable opportunity to explore the field of superpixel segmentation and image processing, as well as to develop essential skills in project management, problem-solving, and critical thinking. The experience gained from this project will undoubtedly be beneficial for future endeavors in both academic and professional settings.
Overall, the project was a success, and the resulting superpixel segmentation solution using K-means clustering and GMM algorithms contributes to the field of image processing and offers valuable insights for future research and development.

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