Light Therapy Project

Mao Ruixuan[1], José Luis Seixas Junior[2]

Eötvös Loránd University

Budapest, Hungary

Abstract

This paper focuses on hyperspectral pixel-wise segmentation, crucial for computer vision applications. Hyperspectral cameras differentiate materials in RGB images due to high spectral resolution. Deep learning, particularly CNNs, achieves promising results by learning from raw data. This study explores clustering algorithms, vital in computer vision. It reviews related works, proposes data normalization and PCA, and evaluates algorithms on Salinas dataset. Hierarchical clustering surpasses DBSCAN and K-means in adaptability and accuracy. These findings advance hyperspectral segmentation, guiding researchers and practitioners in method selection.

---

1. Introduction

Pixel-wise segmentation is a fundamental task in many computer vision applications, including object detection, scene understanding and autonomous driving[1]. Hyperspectral cameras are specialised sensors that capture images with much higher spectral resolution than traditional RGB cameras. These cameras provide a wealth of spectral information that can be used to distinguish between materials that look the same in conventional RGB images.

Pixel segmentation of hyperspectral camera data involves identifying the material composition of each pixel and assigning a label to it, such as vegetation, soil, water or man-made objects. This is a challenging task due to the high dimensionality of hyperspectral data, the presence of noise and atmospheric interference, and the need for accurate spectral signatures for each material class.

However, accurate segmentation of hyperspectral camera data can provide valuable insights for applications such as precision agriculture, mineral exploration and environmental monitoring.

In recent years, deep learning techniques have shown promising results for hyperspectral pixel-wise segmentation, leveraging convolutional neural networks (CNNs) to learn complex features directly from the raw data. These approaches have significantly improved the accuracy and efficiency of hyperspectral segmentation, making it possible to analyze large datasets in real-time.

In this study, the focus is on employing clustering algorithms for pixel-wise segmentation of hyperspectral data, a crucial task in numerous computer vision applications, including object detection, scene understanding, and autonomous driving. Hyperspectral cameras possess superior spectral resolution compared to traditional RGB cameras, offering an extensive array of spectral information. This wealth of data enables the differentiation of materials that exhibit similar appearances in RGB images.

.

2. Realated Works

One of the releated works in this field is A new approach to hyperspectral image segmentation combining conditional random field(CRF) and depth feature learning[2]. The proposed method first uses a convolutional neural network (CNN) to learn depth features from hyperspectral images. Then, the CRF model is applied to the depth features to obtain segmentation results. The proposed method also incorporates spectral-spatial smoothness constraints to improve the segmentation accuracy of hyperspectral images.

The work of Zhang et al. (2018) propose a spectral-spatial hyperspectral image classification method using the K-nearest neighbors (KNN) algorithm. The approach combines spectral and spatial information to achieve competitive classification accuracy, as demonstrated through experiments on public datasets[3].

Another popular approach is the Deep learning, A denoising auto-encoder[4] is used to remove noise from the hyperspectral images, and then a mixed pixel training enhancement method is applied to deal with the mixed pixel problem in the hyperspectral images. Finally, morphological operations are applied to refine the classification results.

Recently, deep learning-based approaches have shown promising results in hyperspectral image segmentation[5]. Proposed method first learns a deep dictionary using a combination of sparse coding and subspace clustering[6], which captures the underlying structure of the hyperspectral image data. Then, a sparse subspace clustering algorithm is applied to the deep dictionary to obtain the classification results.

Additionally, some works have explored a novel hyperspectral image segmentation technique that utilizes graph processing over multilayer networks(MLN)[7]. The method involves constructing a multilayer graph that captures both the spatial and spectral information of the image, which is then partitioned into multiple subgraphs using a graph partitioning algorithm. The resulting subgraphs are further processed using a graph convolutional neural network to obtain accurate segmentation results.

In summary, numerous approaches have been proposed for pixel-wise segmentation of hyperspectral camera images, encompassing classical methods such as deep learning-based approaches and spatial-spectral techniques [8]. Each approach exhibits distinctive strengths and weaknesses, necessitating careful consideration when selecting the most suitable method based on the specific application and data characteristics.

Deep learning-based approaches offer significant strengths in hyperspectral image segmentation[4]. These methods excel at extracting complex features directly from data, enabling the capture of intricate spatial and spectral patterns that may challenge traditional techniques. Leveraging deep learning models, such as convolutional neural networks (CNNs), yields high accuracy and robustness in various computer vision tasks, including hyperspectral image segmentation. Their capacity to automatically extract relevant features and adapt to diverse data distributions makes them particularly well-suited for handling the complex and high-dimensional nature of hyperspectral data.

Nevertheless, deep learning-based approaches also present certain weaknesses. They typically require ample labeled training data to attain optimal performance, which can prove challenging in scenarios where labeled data is scarce or costly to obtain. Training deep learning models demands substantial computational resources and time due to their computational intensity. Moreover, the lack of interpretability in deep learning models can hinder understanding and explaining their decision-making processes.

In contrast, classical spatial-spectral techniques, such as clustering algorithms and spectral unmixing methods, possess their own merits. Clustering algorithms, such as k-means or spectral clustering, effectively group pixels with similar spectral properties, facilitating material identification and segmentation. Spectral unmixing techniques estimate abundance fractions of different materials within each pixel, enabling accurate pixel-wise classification.

However, these classical methods may encounter challenges with complex data distributions and may not fully capture the spatial and spectral correlations present in hyperspectral images. They often rely on assumptions about data distribution or necessitate manual parameter tuning, limiting their adaptability to diverse datasets.

Thus, the choice of method for pixel-wise segmentation should carefully consider the specific requirements, constraints, and characteristics of the application. Deep learning-based approaches excel at capturing complex patterns and achieving high accuracy but necessitate sufficient labeled training data and computational resources. Classical spatial-spectral techniques provide interpretability and can effectively handle certain data characteristics but may be constrained by assumptions and parameter sensitivity. By thoroughly evaluating these factors, researchers and practitioners can make informed decisions when selecting the most appropriate method for their hyperspectral image segmentation task.

3. Method

In this study, we employed a normalization approach for processing the Salinas hyperspectral dataset in order to enhance pixel-wise segmentation. The objective of normalization was to address the scale differences among data from different spectral bands and intensity ranges, while ensuring balanced contributions of each feature to the clustering algorithm. By normalizing the data, we aimed to improve the accuracy and stability of the clustering results.

Unlike normalization, in this study, principal component analysis (PCA) was utilized as a data processing method. PCA is a widely-used dimensionality reduction technique that captures the main variance of the data. It helps in reducing the redundancy of features and extracting the most representative information from hyperspectral datasets. Spectral features across different wavelength bands are crucial for classification and analysis tasks in such datasets. By applying PCA, we aim to retain the essential information while reducing the dimensionality, considering the overall variance of the data. This can improve the performance of clustering and classification algorithms by focusing on the most informative components of the data.

To evaluate the performance of the clustering algorithms, we adopted a comprehensive approach that included rigorous training and testing phases on a carefully selected dataset. This dataset was meticulously curated to encompass diverse spectral features and representative pixel attributes, enabling a thorough assessment of algorithm performance across various scenarios and facilitating informed comparisons.

To quantitatively evaluate the results of each clustering algorithm, we employed a combination of internal and external evaluation measures. Internal evaluation metrics assessed the quality of the generated clusters based on the inherent characteristics and structure of the data. These metrics provided insights into the compactness and separation of the clusters produced by each algorithm. Additionally, external evaluation metrics utilized external information, such as expert annotations or ground truth labels, to assess the alignment between the generated clusters and the true class memberships.

By extensively evaluating and comparing the performance of each clustering algorithm using these objective measures, we were able to identify the most effective approach for our specific application. Based on the internal and external evaluation measures, we selected the algorithms that exhibited the highest performance for further analysis and application in subsequent phases of our research.

Overall, these data processing choices and evaluation strategies aimed to ensure the comparability, stability, and accuracy of the pixel-wise segmentation results in the Salinas hyperspectral dataset.

4. Experiments and Tests

In the implementation and testing phase of this study, a series of procedures were conducted to compare and identify the most suitable clustering algorithm based on both internal and external validation metrics.

To evaluate the performance of the DBSCAN algorithm, a range of epsilon (eps) values ranging from 0.1 to 1.0, with a total of 10 values, was defined. Initially, the data block underwent reshaping, followed by dimensionality reduction through PCA. Subsequently, DBSCAN clustering was applied using different eps values, and for each clustering result, the Silhouette Score and Adjusted Rand Index were calculated.

To visually assess the impact of different eps values on clustering performance, a plot was generated to depict the relationship between eps values and the corresponding Silhouette Score and Adjusted Rand Index. This visualization aided in the selection of an appropriate eps value for clustering by providing insights into the clustering performance under various epsilon settings.

The evaluation then proceeded to the K-Means algorithm, where the Salinas dataset was transformed into a two-dimensional array, and PCA was employed to reduce the dataset's dimensionality. The K-Means algorithm was executed with varying K values, ranging from 2 to 15. Silhouette Coefficient, Calinski-

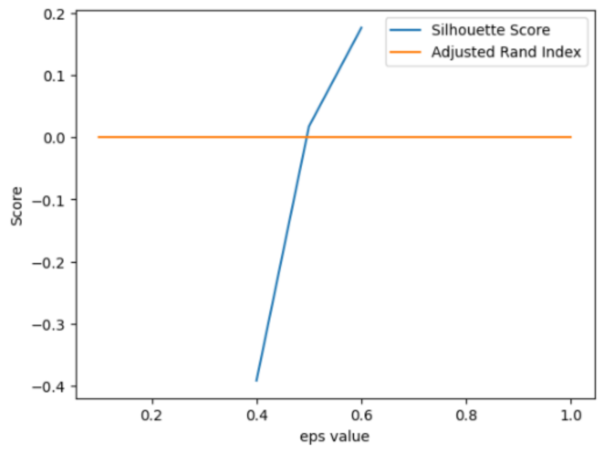

Figure 1: Result of DBSCAN

Harabasz score, and Adjusted Rand Index were computed and subsequently normalized. Plots were created to illustrate the relationship between the K values and the normalized evaluation scores.

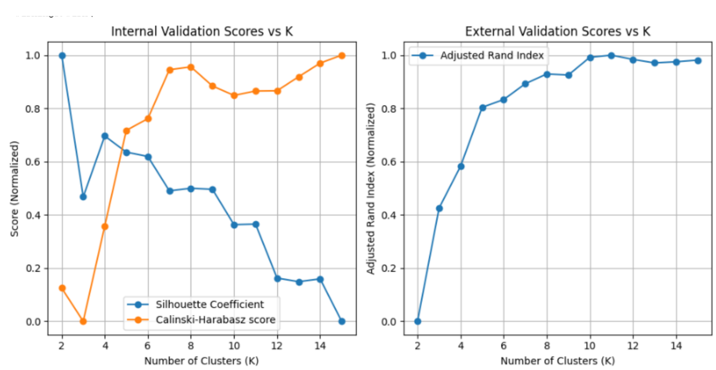

Figure 2: Result of Kmeans

For the Agglomerative Clustering algorithm, the dataset was processed in blocks, with a designated block size and overlap. PCA was applied to each data block, and hierarchical clustering was performed using different linkage methods such as "ward," "complete," and "average." Silhouette Score and Adjusted Rand Index were calculated for each clustering result. Mean Silhouette Score and

Adjusted Rand Index were computed for each linkage method and visualized using a bar chart.

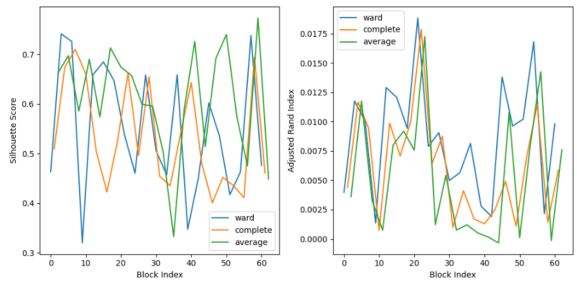

Figure 3: Result of Hierarchical clustering

To compare the performance of the various algorithms, internal validation metrics, namely Silhouette Score and Calinski-Harabasz score, along with the external validation metric, Adjusted Rand Index, were computed and normalized. The normalized scores were utilized to create plots, enabling the evaluation of the algorithms' performance.

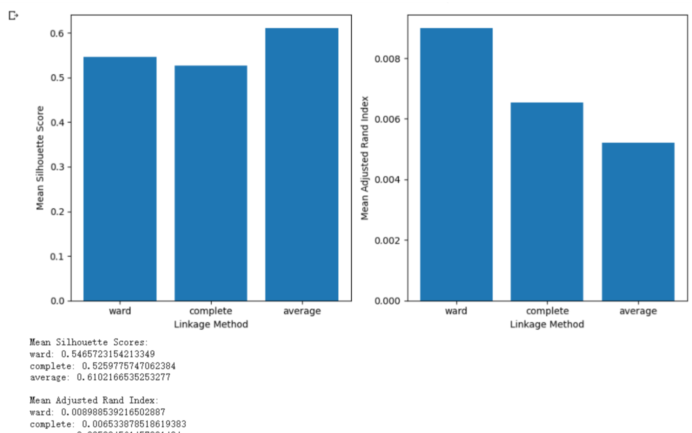

Figure 4: Mean Scores For Different Linkage Type

Based on the evaluation results, the most suitable algorithm was selected by comparing the scores obtained from the different algorithms. The evaluation results, including the Silhouette Score, Adjusted Rand Index, and other relevant metrics, were presented for each algorithm.

In conclusion, the implementation and testing phase involved the application of the DBSCAN, K-Means, and Agglomerative Clustering algorithms to the Salinas dataset. The algorithms were evaluated using various internal and external validation metrics, providing insights into their strengths and weaknesses. This evaluation process facilitated the identification of the most appropriate clustering method for the given dataset.

5. Summary

The hierarchical clustering algorithm exhibits a pronounced advantage over the DBSCAN and K-means algorithms when applied to the Salinas hyperspectral dataset. Its capability to adapt to intricate cluster shapes without relying on shape assumptions enables it to effectively capture the diverse range of cluster shapes present in the dataset, including non-spherical, linear, and fan-shaped clusters. Furthermore, the hierarchical clustering algorithm accounts for density variations among clusters by employing an appropriate linkage method, thereby accurately reflecting density fluctuations within the dataset. Additionally, the hierarchical clustering algorithm provides valuable hierarchical structure information, facilitating in-depth analysis of clustering results at different levels. This approach allows for a comprehensive exploration of the dataset's cluster structure, unveiling relationships and organizational patterns among feature classes. In contrast, the DBSCAN algorithm is highly sensitive to parameter selection, necessitating careful parameter tuning, while the K-means algorithm is sensitive to the initial choice of cluster centers and assumes spherical cluster shapes. These limitations restrict their ability to accurately model the intricate cluster shapes inherent in the Salinas dataset. Consequently, the hierarchical clustering algorithm is deemed superior to the DBSCAN and K-means algorithms for processing the Salinas hyperspectral dataset, as it yields more precise and comprehensive clustering outcomes.

References

[1] S. Bittel, V. Kaiser, M. Teichmann, M. Thoma, Pixel-wise segmentation of street with neural networks (2015). arXiv:1511.00513.

[2] F. I. Alam, J. Zhou, A. W.-C. Liew, X. Jia, J. Chanussot, Y. Gao, Conditional random field and deep feature learning for hyperspectral image segmentationarXiv:1711.04483.

[3] K. Huang, S. Li, X. Kang, L. Fang, Spectral–spatial hyperspectral image classification based on knn, Sensing and Imaging 17 (2016) 1–13.

[4] J. E. Ball, P. Wei, Deep learning hyperspectral image classification using multiple class-based denoising autoencoders, mixed pixel training augmentation, and morphological operations (2018). arXiv:1807.10574.

[5] M. David Jenkins, T. A. Carr, M. I. Iglesias, T. Buggy, G. Morison, A deep convolutional neural network for semantic pixel-wise segmentation of road and pavement surface cracks, in: 2018 26th European Signal Processing Conference (EUSIPCO), 2018, pp. 2120–2124. doi:10.23919/EUSIPCO.2018.8553280.

[6] A. Goel, A. Majumdar, Sparse subspace clustering friendly deep dictionary learning for hyperspectral image classification, IEEE Geoscience and Remote Sensing Letters 19 (2022) 1–5. doi:10.1109/LGRS.2021.3112603.

[7] S. Zhang, Q. Deng, Z. Ding, Hyperspectral image segmentation based on graph processing over multilayer networks (2021). arXiv:2111.15018.

[8] H. Zhang, H. Zhai, L. Zhang, P. Li, Spectral–spatial sparse subspace clustering for hyperspectral remote sensing images, IEEE Transactions on Geoscience and Remote Sensing 54 (6) (2016) 3672–3684. doi:10.1109/TGRS.2016.2524557.