

Deciphering Hyperspectral Image Classification: A Comprehensive Exploration

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Abstract – Hyperspectral imaging is a sophisticated technique that captures multidimensional images of objects by combining imaging and spectroscopic technologies. With hyperspectral imaging (HSI), we can explore both external and internal characteristics of various objects. Each object possesses a unique spectral signature based on variations in reflectance or emittance of its materials. Due to its non-destructive nature, hyperspectral imaging is increasingly penetrating fields such as food production, medical diagnosis, agriculture, pharmaceuticals, recycling, and environmental monitoring. This paper aims to review different methods of hyperspectral image classification, including traditional, deep learning, and pre-trained classifier approaches.

Keywords: Deep learning, CNN, Spectral, Spatial

INTRODUCTION

Classification is the key method in hyperspectral imaging. This is like separating pixels into different groups based on their appearance. This can be done in a variety of ways, such as looking at each pixel individually or using samples to show the computer how different things are. There are different types of hyperspectral imaging, such as those based on the appearance of pixels or the way pixels are combined.

Hyperspectral image classification involves assigning labels to each pixel based on its properties. Similar pixels are grouped into the same category, either based on pixel information or through the use of training samples. [2],[3]. Various methods categorize HSI images based on pixel data, such as Knowledge-based, Per-field, Sub-Pixel, Contextual, Per-Pixel or Multiple Classifiers, approaches. However, classification faces challenges due to the mixed pixels, spectral resemblance, and the multidimensional nature of hyperspectral data. But there are some issues with this approach. Sometimes pixels look similar even though they are actually different, and hyperspectral images come in very different sizes, making them difficult to use. Also, it is easy to obtain the image itself, but it is more difficult to obtain a sample of what is inside the image. [1],[4],[8]. Sometimes image quality can be affected by features such as background noise, making accurate classification difficult. [10],[12].

2. Challenges:

Hyperspectral image classification faces several challenges that make it difficult to accurately sort the images into different categories. [5],[7] These challenges include:

2.1 Spatial Variability:

The appearance of hyperspectral images can change depending on factors like atmospheric conditions, sensor differences, and the distribution of features on the ground. This means that what a pixel represents might not always be clear because it could be influenced by different factors.

2.2 High Dimensionality:

Hyperspectral images have a lot of dimensions because they capture information across hundreds of bands. This makes them complex to work with and requires sophisticated techniques to analyze effectively.

2.3 Lack of Labeled Samples:

While it's relatively easy to obtain hyperspectral image data, it's much harder to get labeled examples of what's in those images. Without these labeled samples, it's challenging to teach the computer how to classify the images accurately.

2.4 Image Quality:

The quality of hyperspectral images can be affected by background noise and other interference during capture. This can impact the accuracy of classification because the data might not be clear enough for the computer to make accurate distinctions.

Overcoming these challenges is crucial for improving the accuracy and reliability of hyperspectral image classification techniques.

3. Machine Learning Methods:

Machine learning includes supervised, unsupervised and semi supervised machine learning.

3.1 Supervised Machine Learning: This method builds a model from labeled training data to classify or predict future data. It utilizes data labeling to guide the machine in recognizing patterns. Examples of supervised learning tools include Artificial Neural Networks, Decision Trees, Support Vector Machines etc.

3.2 Unsupervised Machine Learning: In this approach, the data is unlabelled, and the algorithm seeks to understand the data structure to derive meaningful information. It can perform clustering and dimensionality reduction operations. Examples include Independent Component Analysis (ICA), k-means clustering, Principal Component Analysis (PCA).

3.3 Semi-supervised Machine Learning:

This method uses labeled and unlabeled data to train the classifier. attaching the gap between supervised and unsupervised learning. It combines labeled and unlabeled samples to improve classification accuracy.

4. Hyperspectral Depiction:

The method of capturing and illustrating data from hyperspectral images. The one-dimensional spectral and two-dimensional spatial features of the model are combined to interpret the hyperspectral data.[9] The mathematical expression of the 3D hypercube is

$$x \rightarrow R^b \times (n \times m) \dots(1);$$

Here, b - represents all spectral bands.

n and m represent the spatial components or width and height respectively.[11] Hyperspectral data are shown in Figure 1. In hyperspectral imaging, data is collected across numerous wavelengths, creating a comprehensive representation of the scene under examination. [6]. This approach facilitates the analysis of materials and objects by examining their spectral signatures, which offers valuable information about their composition, characteristics, and spatial arrangement. Hyperspectral depiction finds application in a range of fields including environmental monitoring, agriculture, remote sensing, and medical diagnostics, as it provides detailed insights into the objects or regions being studied.

4.1 Spectral Depiction:

Spectral depiction isolates each pixel array and processes it based on spectral signatures. It aims to achieve better class separability while reducing data dimensionality. Spectral identification process distinguishes each pixel array from other pixels and tracks spectral properties; This means that pixels are characterized only in the spectral space

$$x_i \rightarrow R^b;$$

Here, b - represents the total number of spectral channels or extracts only the necessary ones.

Spectral band transmission using dimensionality reduction (DR) techniques.[14] Techniques include unsupervised methods like supervised methods and Principle Component Analysis (PCA) like Linear Discriminant Analysis (LDA).

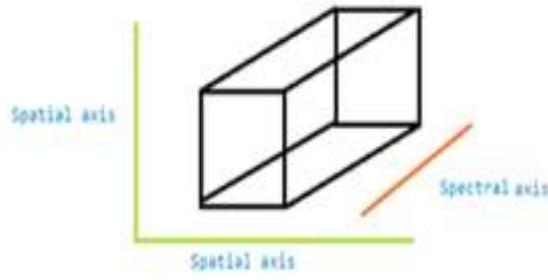


Fig. 1. Hyperspectral Cube.

4.2 Spatial Depiction:

Spatial depiction extracts spatial data from HSI elements to enhance classification accuracy. [15] Spatial recognition methods are evaluated by capturing the spatial information of HSI image elements (pixels) a better relationship. Similar pixels or image elements next to each other belong to the similar class. Methods include Morphological Profiles, Texture Features, and DNN-Based Methods, which combine various techniques for spatial feature extraction.

4.3 Spectral and Spatial Depiction:

This representation provides spectral and spatial information, processing pixel vectors based on spectral properties while considering spatial context. Techniques [16] include processing 3-Dimensional HSI cubes and amalgamating spatial and spectral information for improved classification accuracy.

5 Hyperspectral Image Classification Methods:

A variety of methods are used in hyperspectral image classification, each suitable for specific applications and providing specific results. These methods include:

5.1 Pixel-based classification:

This method involves assigning a label to individual pixels in the hyperspectral image based solely on the spectral features in the hyperspectral images. Although useful, it may not store spatial information well.

5.2 Feature-based classification:

This method uses an extraction technique to identify relevant features in hyperspectral data before classification. These features include metrics, data attributes, or spatial data, thereby improving classification accuracy.

5.3 Spectral Angle Mapper (SAM):

SAM evaluates the angle of a reference spectrum and each pixel's spectral signature for each class. SAM assigns labels to classes related to minimum angles from similar spectral measurements.

5.4 Traditional Methods:

Traditional classification techniques like Support Vector Machines and Random Forests are commonly used. Dimensionality reduction techniques such as ICA and PCA are employed to enhance feature extraction and improve classification results.

5.5 Deep Learning Methods:

Deep learning techniques, such as Auto-encoders and Convolutional Neural Networks, offer advantages in automatically learning features from HSI data and improving classification accuracy.

5.6 Pre-trained Model Methods:

Pre-trained models, like AlexNet and VGG16, provide a starting point for HSI classification tasks. Transfer learning can adapt these models to specific tasks or use them as is.

Research Gap:

Despite advancements, there are still areas requiring further exploration, such as manual feature extraction, high dimensional data analysis, and the integration of spectral and spatial information for classification improvement.

CONCLUSION

Hyperspectral image classification presents challenges in data processing and classification accuracy. Cloud computing offers potential solutions for processing large and complex datasets. Combining spectral and spatial information using deep learning pre-trained techniques can enhance classification accuracy and contribute significantly to the field. Most research focuses on spectral information, but more efforts are needed to incorporate spatial information for better classification results.

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