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Automated Ground Control Point Extraction and Classification of Multi-Temporal Hyperspectral Satellite Imagery

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Abstract

Satellite images based on hyperspectral imagery (HSI) are required to undergo additional processing in order to be utilized in various applications. The classification of hyper-spectral images is a crucial and necessary process for mapping coordinates from the image coordinates. In this procedure, the ground control points (GCPs) need to be manually retrieved from the remotely sensed images, relying on the ground truth values. This particular step is known to be time-consuming. Therefore, this study introduces a method called super pixel based principal component analysis (Super-PCA) for the classification of multi-temporal hyperspectral satellite data. The suggested method aims to automatically extract ground control points (GCPs) and reduce computational time, thereby enhancing classification accuracy. Principal Component Analysis (PCA) is a commonly employed methodology in satellite data analysis for the purpose of feature extraction. However, it is worth noting that the process of extracting features using PCA can be computationally intensive, resulting in slower performance. In order to address the limitations of Principal Component Analysis (PCA), a novel approach known as Super-PCA has been suggested and implemented. However, it is important to note that this technique has mostly been used to images with a relatively low number of features and has not yet been extended to the domain of satellite imagery. In this research, the Super-PCA technique has been enhanced in terms of phase angle for the purpose of feature extraction in multi-temporal hyperspectral satellite imagery at six different levels. The Support Vector Machine (SVM) algorithm is commonly employed in the context of non-linear multi-class classification tasks. The efficacy of Support Vector Machines (SVM) is contingent upon the careful selection of an appropriate kernel. Therefore, the Fuzzy Support Vector Machine (F-RVM) is suggested as a method for selecting the appropriate kernel in satellite imagery analysis, taking into account the resolution and intensity of the features. The obtained results are compared with a range of conventional procedures, demonstrating superior performance.

Keywords: Hyperspectral images, ground control points, principal component analysis, support vector machine.

1. Introduction

The remotely sensed HSI data suffers from various distortions[1] due to the rotation of the satellite, rotation of the earth, sensor calibrations, atmospheric conditions, projection direction, etc. The raw data which is acquired through remote sensing satellites will have too much of errors, noises due to these distortions which will reduce the quality of the acquired image. Hence the satellite images which are directly acquired from the remote satellite are pre-processed for removing the distortions and noises[2]. Thus to overcome this problem, The recent advances in Remote Sensing are towards analysis of the earth surface from time to time for the prediction of natural disasters. Apart from this, change detection also plays a major role in monitoring the environmental conditions. Most of the real time applications with respect to military, daily-life, etc. are based on the remotely sensed data. Remote sensing could be defined as the process by which the information about an object or place or area is acquired without physically having contact with the object or place or area. This is categorized into active remote sensing and passive remote sensing based on the data which is gathered. In passive remote sensing, there are sensors which are usually termed as passive sensors which collect radiation emitted or that is reflected by the object or the area. Usually, passive sensors are designed to measure the sunlight which is reflected. Few examples for passive remote sensing are film photography, infrared, charge-coupled devices[3], radiometers, etc. Active remote sensing is one where they emit energy for the purpose of scanning objects and areas and the sensor detects the amount of radiation that is reflected back from the target. Some examples are RADAR[4], LiDAR[5], etc. Active remote sensing generally relates directly to the process of acquiring images via a satellite. In the Satellite Remote Sensing, the atmosphere plays a major role since the sensors look through this to capture the surface of earth. Hence, the effects of the atmosphere plays a major role in degrading the quality of images acquired. The remotely sensed images are usually in the form of digital images. For the purpose of extracting useful information from these images, image processing techniques are used to enhance the acquired image which helps in visual interpretation and also to correct or restore the distorted, blurred or degraded image. There are various techniques for analyzing the image and the methods that could be used purely depends on the requirement. In most of the cases, image segmentation and classification algorithms are used for creating a thematic map and these are used further with other sources to analyze the test area. The remotely sensed data can be in various resolutions namely Spatial Resolution, Spectral Resolution[6], Radiometric Resolution and Temporal Resolution. 2 Spatial Resolution is helpful in analyzing only a particular field of view. The resolution varies from 0.6 m to 4 m. Spectral Resolution gives the details in the form of color bands and varies in wavelength. Generally the number of Spectral Bands varies from a single band to hundreds of bands. Temporal Resolution is defined by the revisit period of the satellite. It varies from 24 hours to 16 days. Radiometric Resolution varies in the amount of brightness detail.

HSI processing is an advancement of multi-spectral imaging, where the spectra of all the bands are produced as shown in figure 1. The HSI sensor[7] converts the light into electrical signals with the help of few components such as a slit, grating, photo-receptors[8], etc. It is the processing, measurement, and analysis of acquired spectra from the sensors. The basic techniques for HSI image acquisition are spatial scanning, spectral scanning, snapshot or non-scanning and spatio spectral scans. The pixels of the HSI images have more than hundred spectral bands, which contain a large volume of information about the natural objects captured by the satellites.

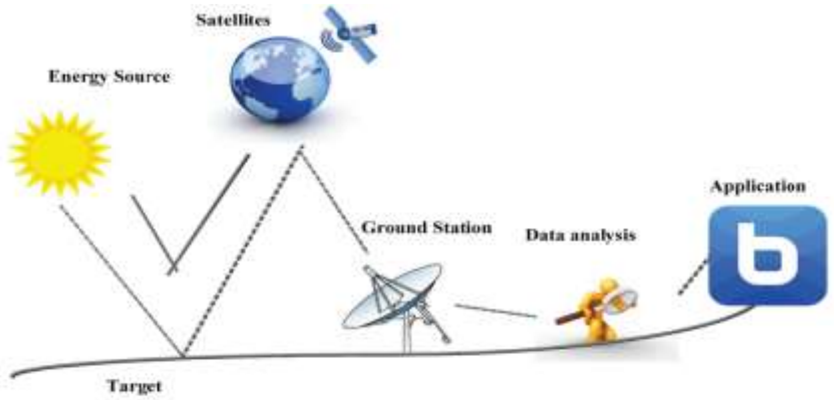


Figure 1: Remote Sensing Architecture

These HSI images consist of hundreds of contiguous narrow bands of data that is enclosed with a large spectrum of reflected light. Generally, a HSI sensor captures satellite or aircraft images. Two types of redundancies exist in the HSI images namely spatial redundancy and spectral redundancy [9]. The relationship between the neighboring pixels of the image is defined by the spatial redundancy. The spectral redundancy describes the correlation between various spectral bands, which occurs in multispectral images or color images [10]. In order to reduce these redundancies, the image compression concept is utilized. Therefore, the bit size of the image is also reduced to moderate the memory usage. By performing the compression, the image is efficiently stored or transmitted to the database.

2. Literature survey:

In [11-12] authors proposed a multihypo thesis prediction based spectral spatial preprocessing technique to eliminate the noise, which in turn enhanced the by grouping different spatially collocated pixel vectors into a hypothesis set. The representational power of the hypothesis set was enhanced by the application of inter band correlation coefficient based spectral-band-partitioning strategy. The predictions were obtained by the combination of various hypothesis sets generated in the previous steps. The multi hypothesis preprocessing was determined using the fisher discriminated ratio. The linear combinations of hypothesis were identified using the Tikhonov regularaization. The proposed technique was compared with the traditional classifiers including LDS-MLE and SVM and found that there was a drastic improvement in the classification accuracy of the proposed technique.

In [13-14] authors proposed automated preprocessing techniques for enhancing the Multivariate Curve Resolution 33 (MCR) of the HSI images. The suggested techniques eliminated the cosmic spikes, detector offsets and structured noise for minimizing the harmful effects of the noise. An optical filter was employed in the preprocessing process to inhibit the intruding of light on the spectral pixels of the images. The light free region of the image was embedded into an imaging system to improve the reduction of structured and detector noise. The spectral information was analyzed to select the spatial regions automatically.

In [15-16] authors proposed a novel preprocessing algorithm to remove the noise and unwanted elements from the HSI images of vessels. Further, a continuum removal algorithm and radiometric correction was used to ignore the redundant criteria from the images. Once the spectra correction was done, the continuum removal algorithm was applied. The qualities of the images were improved by the application of the proposed algorithms. The suggested preprocessing algorithm increased the efficiency of segmentation and classification.

3. PROPOSED METHOD

In the proposed methodology, at first, the given input HSI image is preprocessed by using the PCA method, which is used to reduce the size of the input image for enhancing the given input image based on the gradient spectral and spatial features. Then these enhanced spectral and spatial gradient features based dimensional reduction images are segmented by using the Multi-scale Entropy Rate segmentation (ERS). Then deep features are extracted by using the Super-PCA approach on each segmented area. By utilizing these features SVM based classification performed on HSI images to detect the remote sensing data. The graphical representation of the proposed work is given in Figure 2. The detailed operation of each stage as follows:

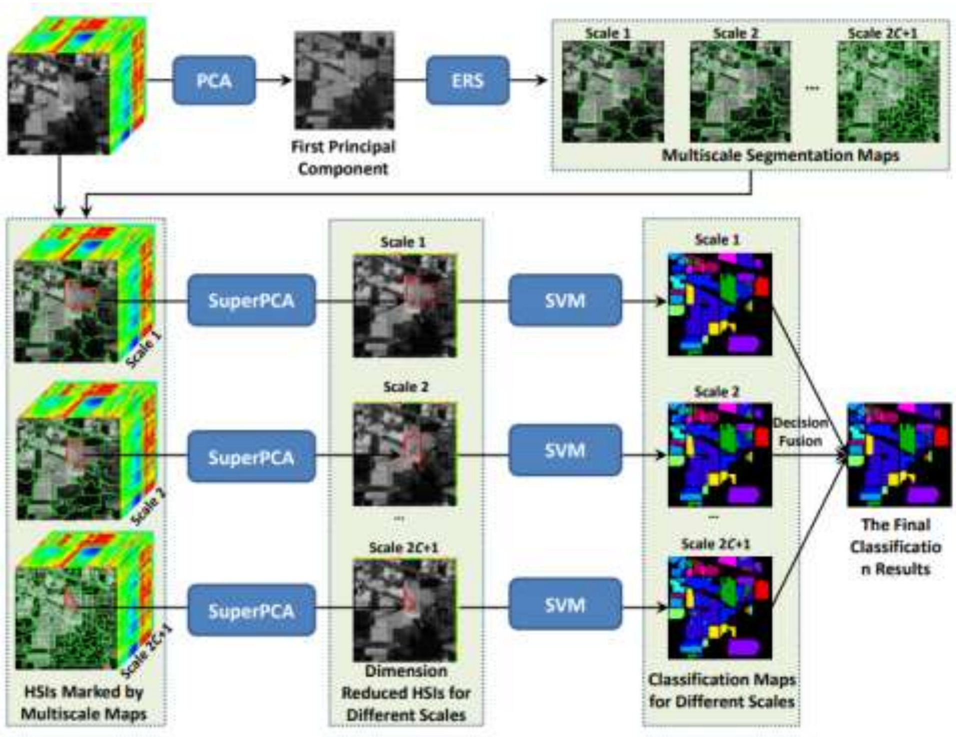


Figure 2: Detection and Classification method of HIS images

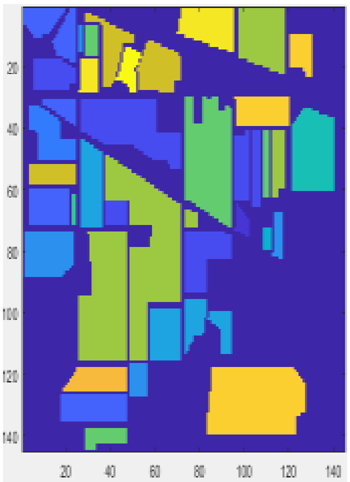
Table 1: Proposed HSI detection and classification algorithm

Input: Collection of input HSI images
Output: Classified features
Step 1: Collect the input HSI images
Step 2: Perform Dimensionality reduction Using PCA
Step 3: perform the Entropy rate super-pixel segmentation
Step 4: perform the Super-PCA based Dimensionality reduction
o Construct the kernel function k and ϕ for the images
o Fine tune features for each hyper feature subspace FS
o Construct the covariance matrix AA
o Characterize the feature subspace FS by projecting the feature
o The expression for the gradient with regard to FS is computed
o Compute the feature subspace after dimensionality reduction
o Update the feature subspace by characterizing them
Step 5: Perform classification using fuzzy based SVM

4. SIMULATION RESULTS

In this work, for the purpose of assessing the results of the proposed approach and existing work, experimental results are obtained with a single data set specifically Indian Pine data set and PaviaU dataset. All the simulations are implemented using Matlab R2018a. From the Figure 3, it is observed that the proposed method perfectly detects and classifies on the Indian Pine data set. The classification of the regions had been done perfectly. For evaluation of quantitative analysis overall accuracy (OA), average accuracy (AA) and Kappa values are calculated and compared with the conventional approaches.

(a)



(b)

(c)

Figure 3: Indian pines dataset (a) input image (b) super-PCA dimensionality reduction image (c) output classified image

Table 2: performance comparison

Method/metric	OA (%)	AA (%)	Kappa

LDA	91.35	89.56	0.9019
EMD-GA	93.485	92.46	0.9156
IEMD-PSO	96.593	95.78	0.924
Proposed	99.04	99.27	0.9886

Table 2 illustrates the outcomes of the complete correctness of the unique data depiction in addition to the fuzzy based SVM classification with spectral improvement, and the dimensionality-reduced features Super-PCA method. It can be found that the overall accuracy results of the proposed method have higher than the existing methods since it reduces the dimensionality of the features by using the Super-PCA methods. From the OA and AA results it is observed that the proposed method provides the better classification results and from the kappa values it is observed that the proposed method has better dimensionality reduction compared to the literatures LDA, EMD-GA and IEMD-PSO and the graphical representation presented in the figure 5 respectively.

Conclusion

This paper explains about a novel Super-PCA based dimensionality reduction method for HSI data. the weight values of kernels are acquired from fuzzy decision approach to optimize the spectral gradient to enhance the classification accuracy of the HIS images. By nonlinearly mapping the HSI images to a higher-dimensional feature space and carrying out Super-PCA on the feature space and obtained higher-order correlations exist in HSI image data. However, in this proposed dimensionality reduction process, there is no focus on the shape of the HSI images. The proposed mixed pixel-wise characterization based Fuzzy SVM method developed for classification of spectral-spatial information. In addition, classification is typically enhanced by fuzzy decision rules. This also increases the dimensionality problem in the HSI’s, and it will reduce the classification accuracy, due to overcoming this dimensionality problem compared to the conventional state of art approaches.

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