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DETECTION OF SUPER-PCA-BASED MACHINE LEARNING STRUCTURES FOR PARTICULAR IMAGES

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Abstract
The satellite photos containing hyperspectral imagery (HSI) are to be further processed for use in any applications. The most crucial and necessary stage requires the classification of hyper-spectral images in order to derive map coordinates from the image co-ordinates. The ground control points (GCPs) for this method must be manually retrieved from the remotely sensed images based on the ground truth values, which takes time. In order to classify the multi-temporal HSI satellite data, super pixel based principal component analysis (Super -PCA) is suggested in this study. This method will automatically extract GCPs and will also shorten the processing time, both of which will boost accuracy. In satellite data feature extraction, PCA is a popular algorithm, however it extracts features relatively slowly. To overcome PCA drawback, Super-PCA is proposed and implemented only for images which has less features but not implemented in satellite images. The Super -PCA is improved in phase angle to be used in satellite data in this research for extracting features for six levels in multi-temporal HSI satellite imagery. Support Vector Machine (SVM) is generally used for non-linear multi-class classification. The accuracy of SVM is based on the kernel selection. Hence Fuzzy SVM (F-RVM) is proposed for kernel selection based on the resolution and intensity of the features in the satellite imagery. The results are compared with various traditional techniques and show the better performance.

Keywords: HSI, Super –PCA, SVM.

1. Introduction

Due to the rotation of the satellite, rotation of the planet, calibrations of the sensors, atmospheric conditions, projection direction, etc., the remotely sensed HSI data is subject to different distortions [1]. Due to these distortions, the raw data collected by remote sensing satellites contains an excessive amount of mistakes and noise, which lowers the quality of the image that is captured. In order to remove distortions and noise, satellite images that are directly obtained from distant satellites are pre-processed [2]. Therefore, in order to solve this issue, current developments in remote sensing are directed occasionally examination of the earth's surface for the forecasting of natural disasters. In addition, change detection is very important for keeping track of the state of the environment. 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.

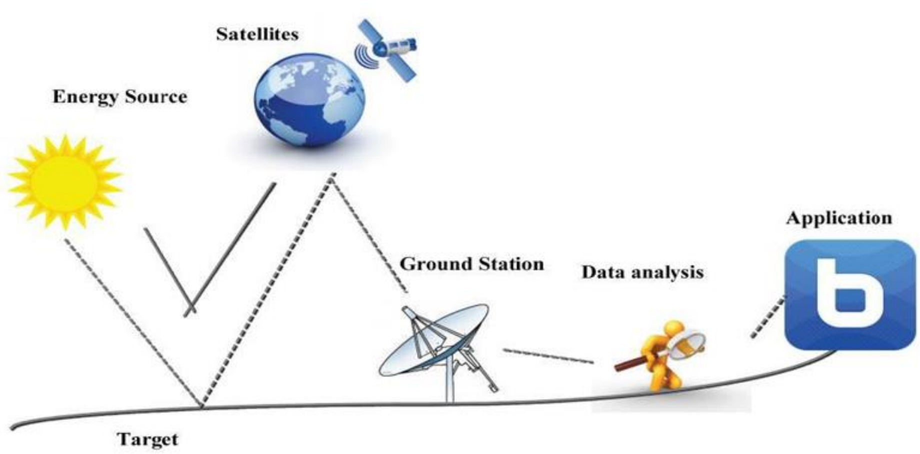

Figure 1: Remote Sensing Architecture

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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.

Rest of this paper as follows, section 2 gives the detailed analysis on multiple related works with their drawbacks. Section 3 gives the detailed operation of proposed detection and classification of hyper spectral images using Super-PCA approach. Section 4 gives the details of experimental results and comparison of quantitative and quality analysis to the conventional approaches and various literatures. Section 5 deals about the conclusion and future implementations of the proposed fusion approach.

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 regularization. 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.

In [17-18] authors surveyed some of the preprocessing techniques to improve the image quality, by removing or reducing the unrelated and surplus parts in the background of the HIS images. Mean or average filter was used to improve the image quality by replacing each pixel with the average value of the intensities in the neighborhood. The limitation was the averaging operation, which led to the blurring of an image. If averaging operations were applied to an image with impulse noise, the noise was not removed but it was diffused. A median filter was a nonlinear filter, and it used the salt and pepper noise in an efficient manner. The median filter was classified as center-weighted median filter, weighted median filter, and max-median filter.

In [19-20] authors presented the advances in spectral-spatial classification by merging the spatial and spectral information of HSI images. The classification was made easier by the use of spatial information of object pixels. The characteristics such as size, contrast and orientation of the images, which was termed as the morphological profile was derived using the mathematical morphology. The additional features required for classification was used to define the morphological neighborhoods. The spectral dimensionality and the spectral-spatial classifiers were the major challenges of HSI 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:

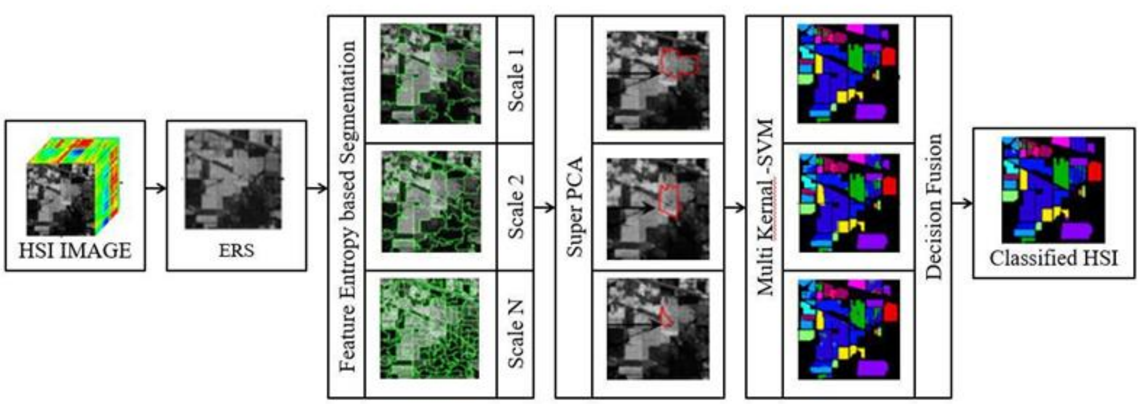

Figure 2: Detection and Classification method of HIS images

3.1 PCA

PCA is performed to remove all the distortions in the image which is acquired from a remote location through remote sensing satellite. The image is distorted due to the climatic changes, reflection and

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refraction due to light rays and rain droplets. The other sources of distortions are due to the calibrations of sensor, projection line, etc. all these distortions reduce the clarity of the acquired image and this forms a source for lesser accuracy in the result of any application. Hence to increase the clarity and remove the distortions available in the image, Cellular Automata based Gaussian Filter Algorithm is proposed which removes all basic noises like Gaussian white noise, speckle noise and all other distortions due to reflections and refractions. In early studies, the basic Gaussian Filter was used in all kinds of Spatial Domain Applications for pre-processing.

This filter helped the researchers in suppression of the basic noises in the remotely acquired satellite data. But the major drawback in using this filter was that there was high level of distortion in the signal after the filtering process was performed. Apart from Spatial Domain applications the Gaussian Filter is widely used in computer vision domain too. The Gaussian filters are of various forms and can be used as per the requirement of the application. It varies from single dimension to multi-dimension
PCA is one of the most extensively utilized dimensionality reduction approaches. It is a commonly accepted approach for eradicating redundancy in the data which depends on decorrelation. Even though it accomplishes redundancy reduction by removal of low variance constituents, this rotational transform is time-consuming as a result of its global nature. Furthermore, since it is a global transformation, it does not maintain local spectral signatures and consequently, might not maintain all information required to obtain a better classification. Extend PCA to consider higher order correlations among the spectral and spatial HSI data pixels for accomplishing improved super-resolution potential.

3.2 ENTROPY RATE SUPER-PIXEL SEGMENTATION (ERS)

"Entropy rate super-pixel segmentation" technique was developed by which comes under unsupervised segmentation technique category. This is not solely based on histogram concept, rather a hybrid technique based on
both region based and thresholding approach. Entropy rate super-pixel region is geometrically a 2-dimensional plane which separates the object part from the background. For illustration, the transition extraction of Eagle image from its original gray image. The transition regions are shown in white, whereas the "foreground and background" are shown in black. Literally, the Entropy rate super-pixel regions separate the foreground from background. The initial Entropy rate super-pixel region has the 3 following properties:

- Region property of HSI: Entropy rate super-pixel region has several pixels width near non step edges whereas single pixel width near step edges.
- Boundary property of HSI: located "between object and background" and covers around the object.
- Gray level variation: gray levels in the transition region usually change frequently and intensively, which leads to abundant information for describing the transition region.

The method developed is based on Effective average Gradient of entropy's. But conventional gradient-based approaches are sensitive to noise and it is applicable to sudden sharp level changes rather than frequent gray level changes. To overcome this limitation various local statistics based approaches were developed by utilizing the Entropy rate super-pixel segmentation. The local region statistics such as Local entropy, modified local entropy, gray level difference were employed subsequently for transition

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region extraction. Those gradient-based approaches for transition region extraction are best suited for sudden gray level changes. But it is not applicable in frequent gray level changes. So, for the images which have frequent gray level changes rather than sudden gray level changes are not suited for gradient-based approaches. Thus, they introduced the information measure content local entropy as a remedy for frequent gray level changes. For an image of size N□M , the local entropy in a m□m local neighborhood is defined as

$$H = -\sum_{i=0}^{L-1} P_i . \log P_i \qquad (1)$$

$$P_i = \frac{n_i}{m\ x\ m} \qquad (2)$$

where, P_i is the probability associated with HSI ith image . n_i is the number of super pixels with gray levels in HSI and L correspond to maximum gray level. The equation 1 indicates that the local variance is more for the heterogeneous region whereas it is less for homogeneous regions. The entropy threshold can be extracted from equation 3 as

$$E_{th} = \alpha H_{max} \qquad (3)$$

where, H_{max} is the maximum entropy of entropy image and α is a coefficient which takes the value in between 0 to

1. For sufficient pixel extraction for transition region, the typical values of α lies between 0.8 to 0.9. The entire algorithm is summarized as follows:
   a. For a definite neighbourhood, compute the local entropy of input image.
   b. Extract "transition region using" entropy threshold.
   c. Find segmentation threshold from the mean of transition region histogram.
   d. Segment the image using segmentation threshold.

3.3 SUPER- PCA

Super-PCA approach is used to effectively reduce the dimensionality in HIS images. The main drawback with conventional PCA dimensionality reduction approaches is that these methods typically showcase linear subspaces (manifolds) present in the data. However to address this issue, dimensionality reduction in nonlinear cases, here this work introduces techniques, including Super PCA with adaptive pixel processing. Hence this work proposes the most popular Dimensionality Reduction (DR) approach than the other approaches such as Super-PCA, as it is user-friendly and simple in terms of application.

As such dimensionality reduction is viewed as a means to attain the degree to which freedom may be deployed in order to engender a fairly large amount of the given input image's data set variability. Dimensionality reduction consequentially on the basis of the high-dimensional image data set generates a compact low-dimensional encoding. HSI Imaging provides a huge number of spectral bands, usually more than 100. This unreasonably large dimension of HSI not only increases the computational 90 complexity but also degrades the classification accuracy of the proposed method. HSI inherently has s significant spectral redundancy measure and also does not have the adequate training data; lowering spectral dimensionality has shown a key factor for facilitating classification algorithms. As such the Super-PCA begins on the basis of a factor analysis solution and then looks and identifies rotations finally leading to independent components.

Super-PCA that generates a sequential array of the best linear approximations that have been given with respect to a high-dimensional observation. This is considered as one of the most accepted techniques in the area of dimensionality reduction. Though, its effectiveness is more ways than one limited on account of global linearity Multidimensional scaling (MDS) again which is associated to PCA which also faces the similar looking. Factor analysis and Independent Component Analysis (ICA) have additionally presumed that underlying manifold is but a linear subspace. These though are demarcated by good quality of the Super-PCA in such a manner that they categorize and replicate subspace. Subspace that had been modeled by Super-PCA captured data characterized by maximum variability and may be seen as modeling data's covariance structure, while factor analysis may be seen as modeling the correlation structure.

Depending on the schemes, characterizes a nonlinear function Φ on the HSI image data sample with feature space R^N as $\Phi:R^N \rightarrow R^{SSF}$ in which we typically characterize the spectral and spatial features as SSF >>NF,R^{SSF} is called as the spectral and spatial feature space. The function Φ is typically selected in order that R^{SSF} includes higher-order product terms from number of HSI features training samples R^N. Employing PCA on R^{SSF} will then acquire higher-order correlations from number of HSI features training samples R^N. On the other hand, samples openly computing the nonlinear map Φ are computationally expensive, particularly when the space is high-dimensional. With the intention of surpassing these complications in PCA, this paper employed super–PCA approach for each number of the HSI data with a nonlinear function.

Given HSI image samples feature vectors in the dimensional space; the RBF kernel function computes their Euclidean square distance among two different HSI feature space vectors in the feature space. In the last step, it is required to carry out the PCA to each HSI feature space and fine-tune the parameters. For that function, it is required to transform the Φ and k to obtain values to each HSI feature space.

By proceeding with the above-mentioned procedure of Super-PCA dimensionality reduction can be done efficiently by eliminating the features that are irrelevant to the system and segregating the classes accurately. In that scenario, the subspace may easily be deployed as input for linear classification models, like the case Fuzzy-SVM classifier because of the limited amount of presence of relevant HSI data's in the system.

3.4 Fuzzy based SVM classification

To enhance the HSI image classification rate, varied pixel-wise probabilistic classification framework approach is carried out in contrast to the Super-PCA technique with respect to the characteristic dimensional space. To promote these kinds of technique, it is mandatory to calculate the spatial and spectral information of the space HSI added with the HSI image gradient level. With the use of Empirical Mode Decomposition based Entropy rate super-pixel segmentation technique, the gradient level spectral data is approximated and to rationalize the spectral information classification done by the use of fuzzy decision SVM.

In this effort, fuzzy decision play a significant role to improve the classification accuracy at gradient level of spatial information, and as a consequence, the calculation of weight values for IMF turns out to be important. This improves the categorization accurateness rate for varied pixel-wise fuzzy decision HSI information.

The improved Fuzzy based SVM classification methods determine the spectral gradient and spatial data for HSI image and performs the probabilistic mixed pixel-wise classification framework. Grounded on the improved EMD, the spectral gradient probability value is approximated, to gain knowledge on the fuzzy-SVM based classifications. Fuzzy sigmoid kernel function is also a method of kernel function which helps to categorize SVM with an aim to improve classification result of HSI descriptions. The efficient differentiation between suitable and inappropriate characteristic vectors can be possible using SVM-FSK method in the course of margin size maximization. The fuzzy sigmoid kernel determines the margin maximization hyperplane which is converted to spatial domain version. This is in fact that utmost margin classifiers are well consistent methods and they do not damage the recital of categorization for infinite dimensional information. We abridge the process of varied pixel-wise Fuzzy-SVM classification arrangement and establish the resemblance among variables utilizing inner result as a metric. In these categorization methods, when any dependent variable subsists, those variables data might be stuck throughout supplementary dimensions, and accordingly, this can be identified by a mapping. The proposed Fuzzy-SVM classification approach can yield improved results in performance of HSI classification when compared to un weighted analyses. Proposed HSI detection and classification algorithm

- **Input:** Collection of input HSI images
- **Output:** Classified features
- **Step 1:** Collect the input HSI images
- **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
- Construct the kernel function k and ϕ for the images
- Fine tune features for each hyper feature subspace FS

  Construct the covariance matrix AA

  Characterize the feature subspace FS by projecting the feature

  The expression for the gradient with regard to FS is computed

  Compute the feature subspace after dimensionality reduction

  Update the feature subspace by characterizing them

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- **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 and figure 4, it is observed that the proposed method perfectly detects and classifies compared on the Indian Pine data set and PaviaU datasets. 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.

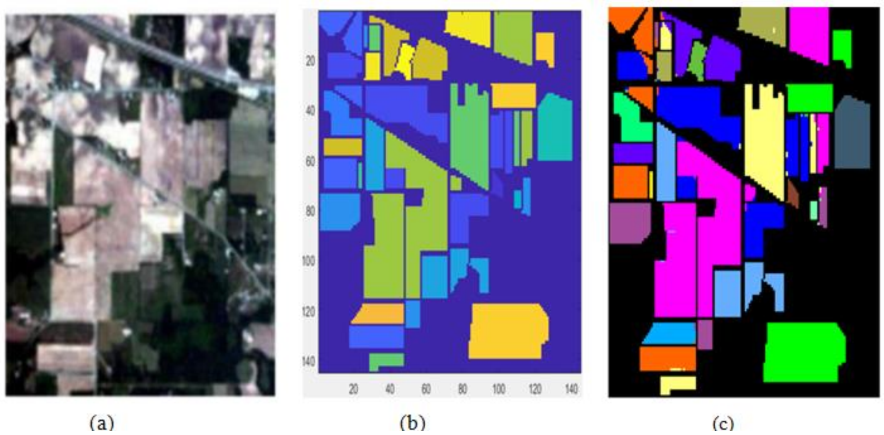

Figure 3: Indian pines dataset (a) input image (b) super-PCA dimensionality reduction image (c) output classified image

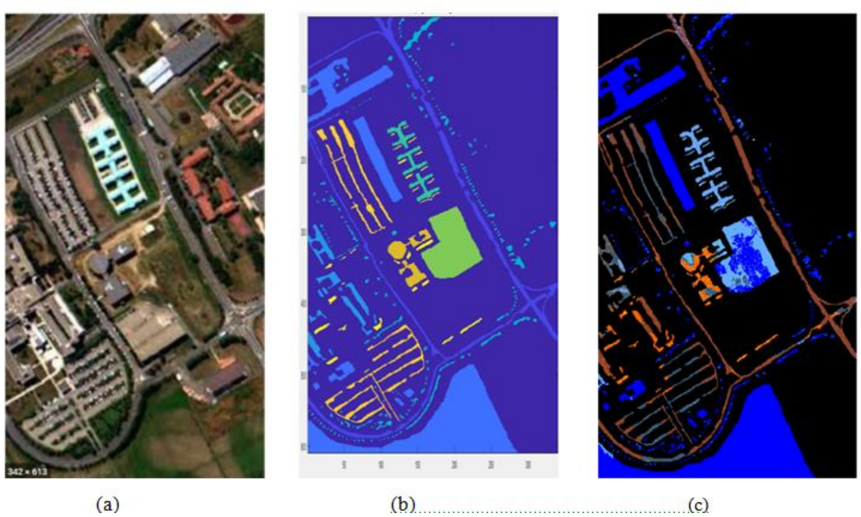

Figure 4: PaviaU dataset (a) input image (b) super-PCA dimensionality reduction image (c) output classified image

Table 2: performance comparison

Method/metric	OA (%)	AA (%)	Kappa
LDA[11]	91.35	89.56	0.9019
EMD-GA[15]	93.485	92.46	0.9156
IEMD-PSO[17]	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 [11], EMD-GA [15] and IEMD-PSO [17] and the graphical representation presented in the figure 5 respectively.

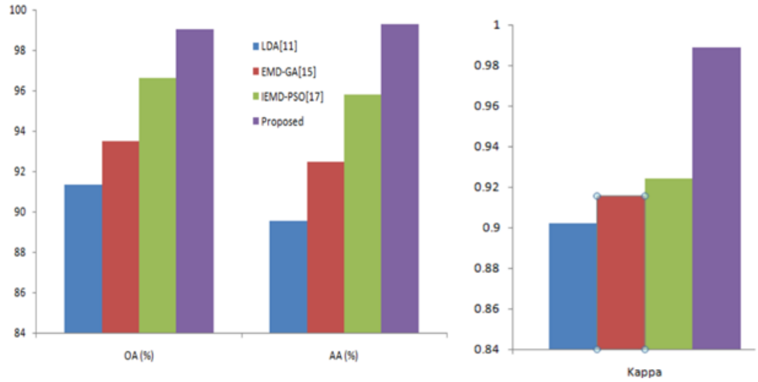

Figure 5: graphical representation of comparisons

Conclusion

This research describes a novel dimensionality reduction method for HSI data based on Super-PCA. In order to optimize the spectral gradient and increase the classification accuracy of the HIS pictures, the weight values of the kernels are obtained using a fuzzy judgment approach. Higher-order correlations can be found in the HSI image data by nonlinearly mapping the HSI images to a higher-dimensional feature space and performing Super-PCA on the feature space. The HSI pictures' shape is not emphasized in this proposed dimensionality reduction procedure, though. The suggested spectral-spatial information categorization approach, which is based on mixed pixel-by-pixel characterization. Additionally, fuzzy decision rules are frequently used to improve classification. 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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