INTERNATIONAL JOURNAL OF TECHO-ENGINEERING
ISSN : 2057-5688

SURVEY ON HYPERSPECTRAL IMAGE CLASSIFICATION USING MACHINE LEARNING ALGORITHMS

[1]SRIKOTI HARIKA, [2]Dr.B. SATEESH KUMAR

[1]M. Tech Scholar, [2]Professor, Department Of CSE,

JNTUH UNIVERSITY COLLEGE OF ENGINEERING, JAGTIAL, T.S., INDIA

ABSTRACT

Hyperspectral image (HSI) processing has been an exciting area in remote sensing as well as other applications in the last few years. Hyperspectral images are a great source of information on spectral properties to identify spectrally similar materials to ensure more precise and precise information extraction. A wide range of sophisticated classification techniques are accessible that are based on spectral data and spatial information. To increase the accuracy of classification, it is crucial to determine and reduce the uncertainties in the image processing chain. This paper reviews the present practices, issues and potential of Hyperspectral Image Classification. Furthermore, significant issues that impact the accuracy of classification are addressed.

Keywords: - Hyperspectral, Image classification, Neural Networks, Accuracy.

1. INTRODUCTION

Hyperspectral imaging gathers data across hundreds of spectrums (which are beyond that of the visible spectrum too) with relatively small bandwidths. With this kind of high resolution, HSI provides ample spectral data to identify and detect distinct patterns in atmospheric and land data with greater precision than can be achieved with other kinds of remotely sensed data. For instance, this Airborne Visible-infrared Imaging Spectrometer (AVIRIS) technology gathers images in 220-224 bands that have 10nm resolution and spectral coverage of 0.4-2.5 um. But this greater number of bands presents challenges to existing methods for analyzing these data. For instance, the high dimension of the data sets creates computational complexity. Therefore, reducing the dimension without losing any information is a major concern. Another crucial issue is the gathering of training samples with labels that require a costly ground campaign. This leads to high numbers of spectral bands and a little labeled training samples. This causes the well-known Hughes phenomenon.

Recently Deep Learning (DL) grows rapidly with the growth of computers. Convolutional Neural Network (CNN) is a key algorithm in deep learning [6], that has the ability to perform feature learning. The design of its structure makes it a great choice for solving problems in the image space [7, 8]. CNN can effectively extract features through local connections and can decrease the amount of parameters used by sharing weight. The applications of image classification [8] as well as target detection [9] and super-resolution reconstruction of images [10] provide the base for the HSI classification tasks. However, this high resolution as well as the long retention of information leads to an increase in data dimensions and redundant spatial data, which results in low computational efficiency. With the increase of dimension, the accuracy of classification will increase at first, but then decrease significantly called Hughes phenomenon[11]. So, how can we improve the accuracy in classification of HSI using the spectral-spatial data of HSI in the context of ensuring computing efficiency is a major issue.

2. HYPERSPECTRAL IMAGE CLASSIFICATION METHODS

The main goal of image classification is to automatically classify every pixel in an image as a land cover category. Based on the information about pixel size Images are classified as Per-pixel, Sub-pixel Per-field, Knowledge-based contextual, and multiple classifiers. Per-pixel classifiers could be non-parametric or parametric. Based on the examples of training, images may be classified into Supervised category or Unsupervised category Classification. Unsupervised classification involves the recognition of natural structures or groups. Controlled classification is the method that uses samples of certain identities to categorize to assign pixels that are not classified to one of the informational classes. The supervised method is based on the steps like feature extraction, training, and labeling procedures. The first step involves changing the image into an image that features to decrease the dimensions of the data and enhance the interpretability of the data. This process is not required and includes methods such as HSI transformation principal component analysis and linear mixture models. In the phase of training, there is a set of samples from the image is chosen to define every class. The training samples are used to train the classifier to distinguish the classes. They are then used to determine the "rules that allow assigning labels for each class individual pixel of the image.

ISSN : 2057-5688

2.1. Band selection method

Every HSI scenario is represented with an image cube, where the third dimension is the spectrum. This results in massive amounts of data that computers can process and transmit. In the literature, numerous criteria, such as divergence, for example were introduced to aid in the selection of bands to determine the bands that are vital and important in terms of information conservation. In [11], suggests an approach to selecting bands that operates in two phases: 1) The prioritization of bands in which bands were given priority based on the information, based on the eigenanalysis method, and 2) band decorrelation, in which divergence was employed to create a decorrelation between prioritized bands. The band selection process was achieved using an eigenanalysis-based band prioritization method in combination with the divergence-based decorrelation of bands [14].

2.2. Kernel-based methods

The survey reveals that a variety of automated algorithms to aid in HSI classification were developed by different researchers employing Artificial Neural Network (ANN), Radial Basis Function Neural Networks (RBFNNs) [13]-[15]. One of the main challenges in the HSI dataset is a large number of spectral bands as well as a little trained samples that are labeled that pose the well-known issue of the problem of dimensionality, commonly referred to as Hughes phenomenon [1] in research literature. To solve this issue, researchers turned to Kernel techniques that include the Support Vector Machines (SVMs) or Kernel Fisher Discriminant [KFD] analysis. They were able achieve excellent results in terms of accuracy and robustness.

2.3. Semi supervised learning methods

In [13], proposed a semi-supervised method of classification that utilized both labeled as well as unlabeled samples to tackle the issue of the unsolved (also called Hughes phenomenon) that occur mostly due to the small size of training sets, which may cause the over and under-fitting of algorithms used in learning. They utilized semi-supervised SVMs, also known as transductive SVMs (TSVMs), an iterative algorithm that slowly look for a reliable separating hyperplane using Transductive processes that include both unlabeled and labeled samples in the training phase. This proposed TSVM classifier was able to combine the benefits of semi-supervised methods and kernel-based techniques.

2.4. Multinomial logistic regression-based methods

Sparse Multinomial Logistic Regression is a different method that was developed in the field of HSI processing. Multinomial logistic regression offers the benefit of learning the class distributions on its own. In [8] presented a semi-supervised segmentation and classification technique that relies on sparse multinomial logistic regression [88]. They considered both spatial and spectral aspects to improve the results of classification. The contextual information that is inherent to the spatial configuration of image pixels was captured by the Multi-Level Logistic (MLL) Markov- Gibbs random field. The algorithm was implemented using two steps: 1) a learning process to discover the distributions of class as well as 2) segmentation using inferring labels of the posterior distribution, based upon the class distributions learned and MLL prior. The distributions of classes were constructed using multinomial logistic regression which computes the regressors by using the LORSAL (Logistic Regression Using Variable Splitting and Augmented Lagrangian) algorithm.

Table 1: Findings of different methods in HSI analysis

Method	Findings
Band Selection	As high as 94 percent of bands had been reduced in order to give nearly the same results in classification.
Kernel Based Methods	These methods showed excellent results in regard to precision, computation cost, and robustness. Composite kernels could achieve 98.86 percent classification accuracy.
Semi Supervised Learning Algorithms	These methods demonstrated an 8.86 improve -ment over the methods with supervision, when using a very small number of training samples
Multinomial Logistic Regression	Semi-supervised algorithms employing MLL demonstrated significant improvements in the accuracy of classification as compared with supervised algorithms working with a small number of training samples
3-D Gabor Filter	These techniques considered both spatial and spectral features and resulted in 94.66 percent accuracy with only five percent of the available samples.

Tensors	As high as 97.66 percent accuracy of classification was obtained with these methods.
Pruned BPT	The methods demonstrated an improvement of 47% in the accuracy of classification over regular SVM.

3. HYPERSPECTRAL IMAGES CLASSIFICATION

The HSI classification process is shown in Figure 1 The classification process consists of the major steps of data input, data preprocessing, feature information extraction and feature map activation, classification model, accuracy evaluation, and classification results.

The preprocessing of HSI mainly includes image format conversion, geometric correction, noise reduction, dimensionality reduction, etc. The purpose is to eliminate noise and reduce the complexity of HSI as much as possible to improve the operation efficiency and provide data for the subsequent classification model.

Feature extraction and feature selection is also essentially a dimensionality reduction, a process of finding the optimal solution, and commonly used methods include Principal Components Analysis (PCA), which uses linear transformations to extract features, but hyperspectral data is inherently nonlinear, so linear transformation methods such as PCA can lose a lot of useful information. Choosing a suitable feature extraction and classification model is the key to achieve high classification accuracy. Traditional methods can only extract limited spectral feature information, while the spatial-spectral joint feature classification-based methods can extract not only spectral feature information but also spatial feature information and perform effective feature fusion, which can effectively fit the nonlinear relationship between the classification labels of high HSI and HSI data features for high dimensional data like HSI to obtain better classification results. On the other hand, the joint spatial-spectral feature classification model integrates feature extraction and feature classification into one framework, which can achieve end-to-end training.

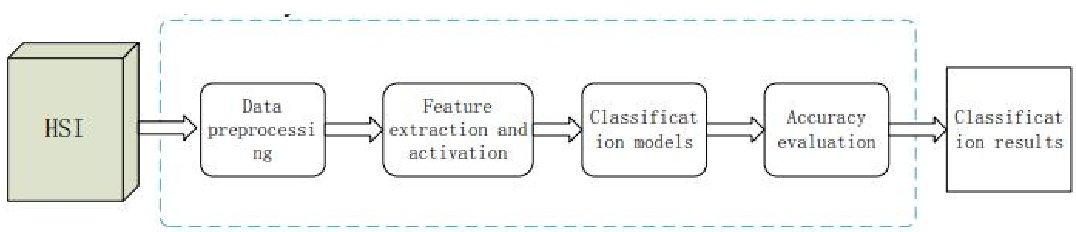

Figure 1. Hyperspectral images classification process

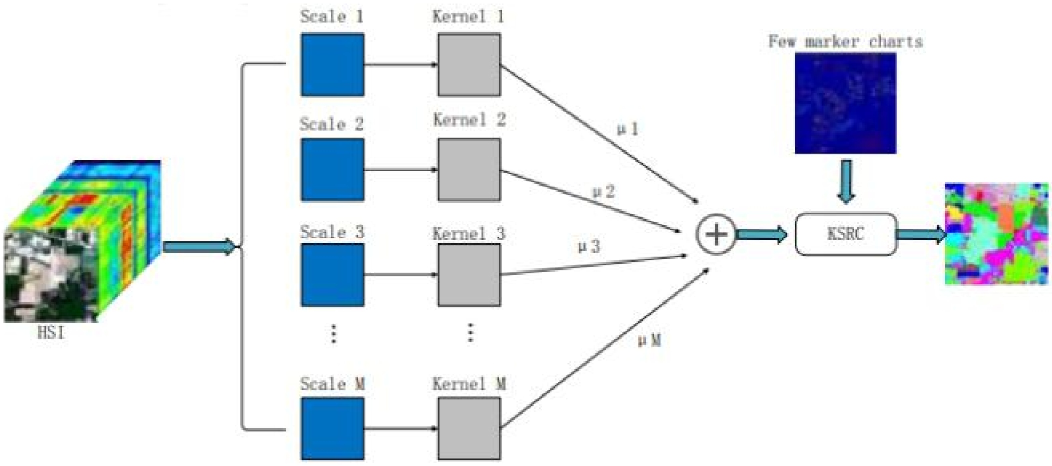

Figure 2. Hyperspectral images classification model based on multi-core fusion

Traditional methods can only extract limited spectral feature information, while the spatial spectral joint feature classification-based methods can extract not only spectral feature information but also spatial feature information and perform effective feature fusion, which can effectively fit the nonlinear relationship between the classification labels of high HSI and HSI data features for high dimensional data like HSI to obtain better classification results. On the other hand, the joint spatial spectral feature classification model integrates feature extraction and feature classification into one framework, which can achieve end-to-end training.

4. CONCLUSION

Over time, many methods have been developed by researchers to address the difficulties in the field of HSI analysis. Table 1 summarizes the results of the various methods described in this article. While hyperspectral imaging can be an incredible source of data in the manner discussed, it does have some fundamental issues that need to be dealt with. Processing of large-scale data and limited access to training samples are the major problems in this area. Researchers are working on the area of reduction of dimensions. While the use of semi-supervised algorithms and SVMs has helped solve the second problem to a certain degree but this field remains open to research.

REFERENCES:

[1] ZHU Shulong, ZHANG Zhanmu. The acquisition and analysis of remote sensing image[M]. Beijing: Science Press, 2000.

[2] ZHANG Xuan, HAO Minglei, XING Hongyan, er al. Research on de-speckling of SAR image. based on 3D matching block［J］. Journal Electronic Measurement and Instrumentation, 2017, 31(10)1621-1626.

[3] Zeng Z, Cumming I. Modified SPIHT Encoding for SAR Image Data[J]. IEEE Transactions on Geoence & Remote Sensing,2001, 39(3) : 546-522.

[4] FU Suining, LU Xiaoping, LU Yao. ROF Partial Differential Equations Suitable for SAR Images. De-noising[J]. Bulletin of Surveying and Mapping, 2018(11):16-19.

[5] XU Dongdong， CHENG Deqiang， CHEN Liangliang， et al. Hyperspectral image classification. based on hierarchical guidance filtering and nearest regularized subspace[J]. Acta Photonica Sinica, 2020, 49(4):197-209.

[6] XIE S， GIRSHICK R， DOLLAR P， et al. Aggregated residual transformations for deep neural. networks［C］. IEEE Conference on Computer Vision and Pattern Recognition，2016.

[7] ZHANG Hui, DU Yu, NING Shurong. Pedestrian detection method based on Faster RCNN[J]. Transducer and Microsystem Technologies, 2019,38(2): 147-149,153.

[8] LI Hua, YANG Jianeng, LIU Feng, et al. Survey of Breast Cancer Histopathology Image. Classification Based on Deep Learning[J]. Computer Engineering and Applications, 2020,56(13) :1-11.

[9] REN S， HE K， GIRSHICK R， et al. Faster R-CNN： towards real-time object detection with. region proposal networks[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence， 2017, 39(6):1137-1149.

[10] NAN F， ZENG Q， XING Y， et al. Single image super-resolution reconstruction based on the. ResNeXt network[J]. Multimedia Tools and Applications, 2020, 79(7) : 34459-34470.

[11] HUGHES G F. On the mean accuracy of statistical pattern recognition［J］. IEEE Trans on. Inform Theory(IT), 1968, 14:55－63.

[12] ZHANG J., WEI F., FENG F., et al. Spatial-spectral feature refinement for hyperspectral image. classification based on attention-dense 3D-2D-CNN [J]. Sensors (Basel), 2020, 20(18): 5191.

[13] Chen Y S, Jiang H L, Li C Y, et al. Deep feature extraction and classification of hyperspectral. images based on convolutional neural networks [J]. IEEE Transactions on Geoence & Remote Sensing, 2016, 54(10): 6232-6251.

[14] Hamida A B , Benoit A , Lambert P , et al. 3-D deep learning approach for remote sensing image. classification[J]. IEEE Transactions on Geoence & Remote Sensing, 2018, 56(8):4420- 4434.

ISSN : 2057-5688

[15] LIU B， YU X， ZHANG P， et al. A semi-supervised convolutional neural network for. hyperspectral image classification[J]. Remote Sensing Letters，2017, 8(9) : 839-848.

[16] LI Ying，ZHANG Haokui，SHEN Qiang. Spectral-spatial classification of hyperspectral imagery. with 3D convolutional neural network[J]. Remote Sensing，2017, 9(1):67.

[17] H. Lee，H. Kwon，Going Deeper With Contextual CNN for Hyperspectral Image Classification[J]. IEEE Transactions on Image Processing，2017, 26(10).

[18] HE K M，ZHANG X Y，REN S Q，et al. Deep residual learning for image recognition ［C］. IEEE Conference on Computer Vision and Pattern Recognition,2016 : 770-778.

[19] W. Song，S. Li，L. Fang，and T. Lu，Hyperspectral image classification with deep feature. fusion network. IEEE Transactions on Geoence & Remote Sensing, 2018, 56(6), 3173-3184.