JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Vector Classifier - An Amalgamated method for Hyper Spectral Image classification

Phulen Mahato

Assistant Professor
Department of Computer Science
Barrackpore Rastraguru Surendranath College, Barrackpore, Kolkata-120, India.

Abstract : In this work, a methodology been proposed for classification of a user fed HSI image into a predefined group. To achieve our target at first a data base of image group is constructed. The methodology begins with feeding an unknown image by user. This raw image consists of many noises, hence a data preprocessing is carried out for noise removal, followed by a procedure for band reduction. Here we have incorporated a methodology for reduction of the number of bands from 200 to 50, resulting in an improvement in execution time. Finally incorporating the concept of a vector machine, the target classification has obtained. The proposed method is quiet successful for image classification in comparison of some popular image classification methods.

***IndexTerms* - HSI image classification, noise removal, data preprocessing, band reduction, vector machine.**

I. INTRODUCTION

Hyperspectral image is a 3D data cube, which contains two-dimensional spatial information (image feature) and one-dimensional spectral information (spectral-bands). The basic aim of hyper spectral image classification is to assign a class label to each pixel for a set of observations with known class labels. In this proposed work at first a database of classes for known images been developed. The methodology begins with feeding a unknown raw HIS image. Obviously these images contain a good amount of noises. Hence at the very beginning we have incorporated the procedure for data cleaning. Now this cleaned HSI image is considered as the actual input. This HSI input image has 200 spectral bands. Considering all of them results a good amount of execution time during classification. Hence a methodology for band reduction is applied. Applying the concept of Component Analysis, we have reduced the number of spectral bands from 200 to 50, i.e. a reduction of 1/4th of the original band sizes been achieved. Later for classification, the concept of vector machine has come on to the crease. The reason behind taking a vector machine for image classification is that, it works well with high-dimensional spaces, as well as its very much memory efficient.

II. PRELIMINARIES

This section deals with some fundamental concepts used for achieving the goal of HSI image classification.

First one concept is Hyperspectral image (HSI). HSI image is a 3D data cube, which contains two-dimensional spatial information (image feature) and one-dimensional spectral information (spectral-bands).

The term classification is used to denote the process that assigns individual pixels to a set of classes. The output of the classification step is known as the classification map. HSI image classification always suffers from varieties of artifacts, such as high dimensionality, limited or unbalanced training samples, spectral variability, and mixing pixels. The power of classification increases with the increase of available training samples. The limited availability of training samples decreases the classification performance with the increase of feature dimension. It is well known that increasing data dimensionality and high redundancy between features might cause problems during data analysis. There are many significant challenges that need to be addressed when performing HSI image classification.

Next one concept been used here is Component Analysis. It is the most widely used technique for dimensionality reduction. In comparative sense, appreciable reduction in the number of variables is possible while retaining most of the information contained by the original dataset. The analysis attempts to eliminate the correlation between the bands and further determines the optimum linear combination of the original bands accounting for the variation of pixel values in an image.

Finally the concept of Vector Machine been applied for the work. Support Vector Machine(SVM) is typically a linear classifier associative with kernel functions and optimization theory and is prominent for HSI classification. SVM handling non-linearly seperable data are efficient in the sense that it transforms these data into a higher dimensional space to make them linearly seperable. SVM outperforms the conventional supervised classification methods particularly in prevailing conditions like increased number of spectral bands and the limited availability of training samples. .

III. METHODOLOGY

The following figure 1 shows a flow chart of the methodology been proposed here for classification of the HSI image.

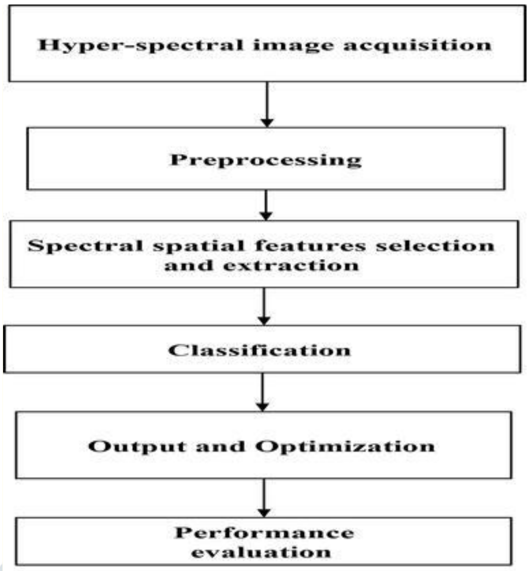

Fig. 1: Flow chart of the procrdure

The methodology begins with formation of database consisting of well-known images with their known classes. Next an input unknown image is fed. As this image may contain a good amount of noises, hence we have applied some procedures for reduction of noises. This noise free image actually is considered as the real input. Next methodology of band reduction is applied on this input image. The number of spectral bands in this input image is 200, which is reduced to $1/4^{th}$ of its original number, i.e. at 50; by incorporation of the method of component analysis; resulting a large improvement in the execution time during classification. Finally the reduced image is passed through a vector machine to achieve the target class.

IV. RESULTS

For execution of the methodology mentioned above we have considered a machine with specifications 4 GB RAM and INTEL Core i3 Processor. The method been implemented using Python Jupiter Notebook IDE.

The constructed database taken into consideration for classification consists of 16 classes , around 10000 specimens altogether. Which clearly means the proposed methodology will place the unknown fed image into anyone of these 16 classes.

After execution of the proposed methodology on the fed HSI image, the following classification report is generated. (Table 1).

Table 1: Classification report

	precision	recall	f1-score	support
Alfalfa	0.89	0.89	0.89	9
Corn-notill	0.87	0.84	0.85	286
Corn-mintill	0.89	0.82	0.86	166
Corn	0.74	0.74	0.74	47
Grass-pasture	0.92	0.96	0.94	97
Grass-trees	0.98	0.95	0.97	146
Grass-pasture-mowed	1	0.8	0.89	5
Hay-windrowed	0.99	0.99	0.99	96
Oats	0.5	0.5	0.5	4
Soybean-notill	0.89	0.84	0.86	194
Soybean-mintill	0.86	0.92	0.89	491
Soybean-clean	0.88	0.91	0.89	119
Wheat	0.93	1	0.96	41
Woods	0.96	0.98	0.97	253
Buildings Grass Trees Drives	0.86	0.7	0.77	77
Stone Steel Towers	1	1	1	19

The accuracy, weighted average and macro average as obtained from classification report is mentioned in table 2.

Accuracy			0.9	2050
Macro avg	0.88	0.87	0.87	2050
Weighted avg	0.9	0.9	0.9	2050

Figure 2 shows the confusion matrix generated.

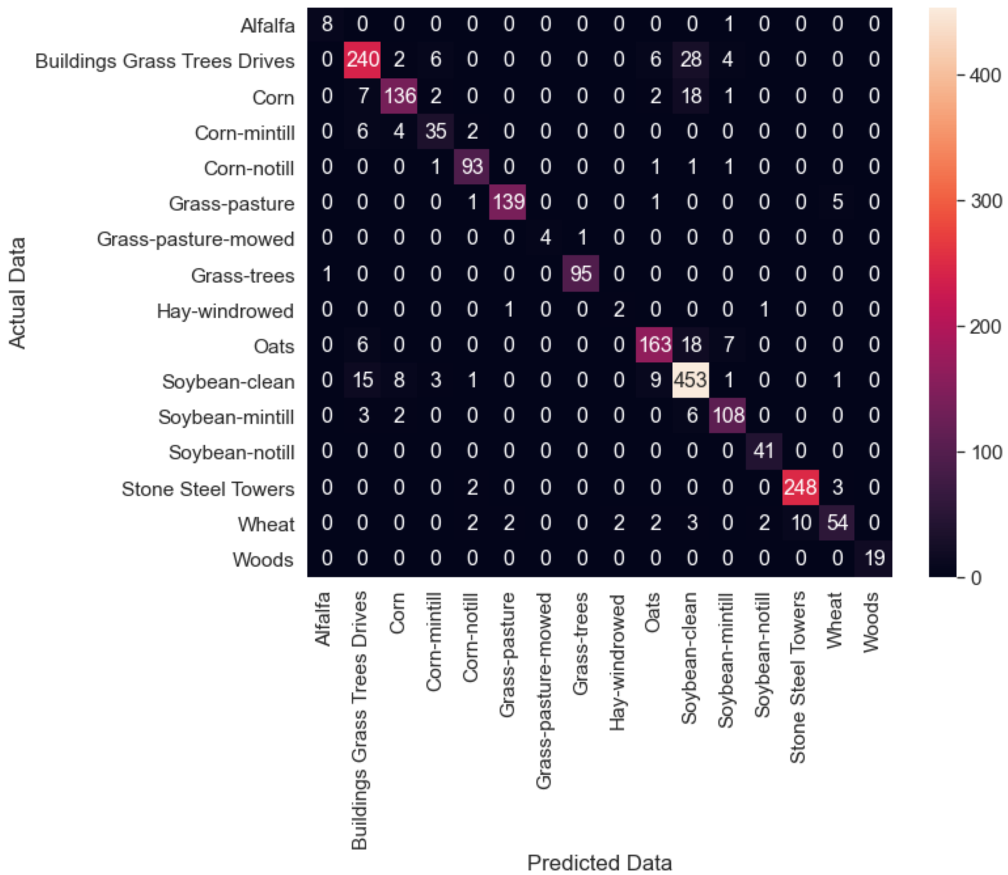

Figure 2: Confusion Matrix

Finally the classification map is depicted in figure 3.

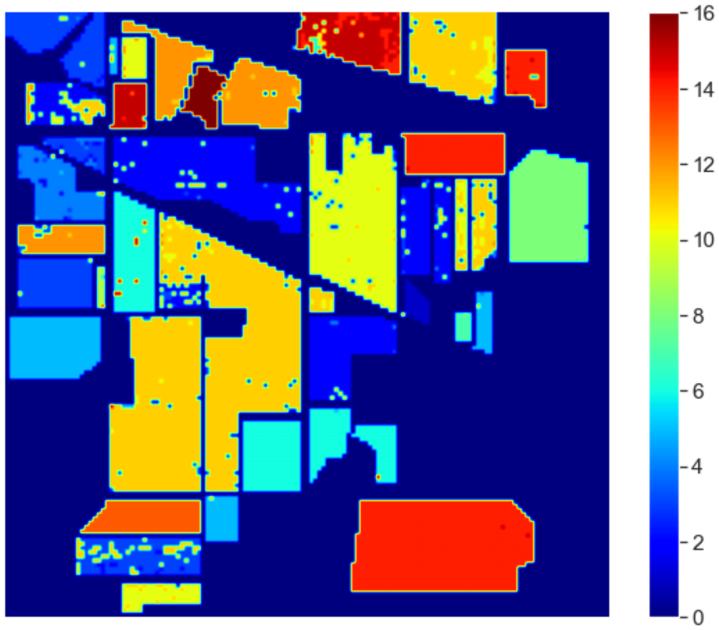

Figure 3: Classification Map

IV. CONCLUSION

This proposed method works very efficiently for classification of HSI image. Here incorporation of noise removal makes it suitable for dealing with any image, no matter how much noisy is it. The procedure for band reduction to 1/4th of the original size has improved the execution time to a great extent. Finally incorporation of vector machine enables the methodology to work with high dimensional space and reduction in memory need.

REFERENCES

1. Bioucas-Dias JM, Plaza A, Camps-Valls G, Scheunders P, Nasrabadi N, Chanussot J. Hyperspectral remote sensing data analysis and future challenges. IEEE Geoscience and remote sensing magazine. 2013;1(2):6-36

2. Tong X, Xie H, Weng Q. Urban land cover classification with airborne hyperspectral data: What features to use? IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2013;7(10):3998-4009

3. Gevaert CM, Suomalainen J, Tang J, Kooistra L. Generation of spectral–temporal response surfaces by combining multispectral satellite and hyperspectral uav imagery for precision agriculture applications. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. 2015;8(6):3140-3146

4. Yuen PW, Richardson M. An introduction to hyperspectral imaging and its application for security, surveillance and target acquisition. The Imaging Science Journal. 2010;58(5):241-253

5. Zhang L, Zhang L, Tao D, Huang X, Du B. Hyperspectral remote sensing image subpixel target detection based on supervised metric learning. IEEE Transactions on Geoscience and Remote Sensing. 2014;52(8):4955-4965

6. Yang X, Yu Y. Estimating soil salinity under various moisture conditions: An experimental study. IEEE Transactions on Geoscience and Remote Sensing. 2017;55(5):2525-2533

7. Shahshahani BM, Landgrebe DA. The effect of unlabeled samples in reducing the small sample size problem and mitigating the Hughes phenomenon. IEEE Transactions on Geoscience and Remote Sensing. 1994;32(5):1087-1095

8. Chi M, Bruzzone L. Semisupervised classification of hyperspectral images by svms optimized in the primal. IEEE Transactions on Geoscience and Remote Sensing. 2007;45(6):1870-1880

9. Hughes G. On the mean accuracy of statistical pattern recognizers. IEEE Transactions on Information Theory. 1968;14(1):55-63

10. Jin J, Wang B, Zhang L. A novel approach based on fisher discriminant null space for decomposition of mixed pixels in hyperspectral imagery. IEEE Geoscience and Remote Sensing Letters. 2010;7(4):699-703

11. Zhang L, Zhang L, Tao D, Huang X. On combining multiple features for hyperspectral remote sensing image classification. IEEE Transactions on Geoscience and Remote Sensing. 2011;50(3):879-893

12. Zhong Y, Zhang L. An adaptive artificial immune network for supervised classification of multi−/hyperspectral remote sensing imagery. IEEE Transactions on Geoscience and Remote Sensing. 2012;50(3):894-909

13. Melgani F, Bruzzone L. Classification of hyperspectral remote sensing images with support vector machines. IEEE Transactions on Geoscience and Remote Sensing. 2004;42(8):1778-1790

14. Mohamed RM, Farag AA. Advanced algorithms for bayesian classification in high dimensional spaces with applications in hyperspectral image segmentation. In: IEEE International Conference on Image Processing. Vol. 2. IEEE; 2005. pp. II-646

15. Camps-Valls G, Gomez-Chova L, Muñoz-Marí J, Vila-Francés J, Calpe-Maravilla J. Composite kernels for hyperspectral image classification. IEEE Geoscience and Remote Sensing Letters. 2006;3(1):93-97

16. Wold S, Esbensen K, Geladi P. Principal component analysis. Chemometrics and Intelligent Laboratory Systems. 1987;2(1–3):37-52

17. Hyvärinen A, Oja E. Independent component analysis: Algorithms and applications. Neural Networks. 2000;13(4–5):411-430

18. Rodarmel C, Shan J. Principal component analysis for hyperspectral image classification. Surveying and Land Information Science. 2002;62(2):115-122

19. Villa A, Benediktsson JA, Chanussot J, Jutten C. Hyperspectral image classification with independent component discriminant analysis. IEEE Transactions on Geoscience and Remote Sensing. 2011;49(12):4865-4876

20. Li C, Yin J, Zhao J. Using improved Ica method for hyperspectral data classification. Arabian Journal for Science and Engineering. 2014;39(1):181-189

21. Du P, Liu P, Xia J, Feng L, Liu S, Tan K, et al. Remote sensing image interpretation for urban environment analysis: Methods, system and examples. Remote Sensing. 2014;6(10):9458-9474