AUTOMATIC TARGET DETECTION IN HYPERSPECTRAL IMAGES USING NEURAL NETWORK

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Abstract

Spectral analysis of remotely sensed images provide the required information accurately even for small targets. Hence Hyperspectral imaging is being used which follows the technique of dividing images into bands. These Hyperspectral images find their applications in agriculture, biomedical, marine analysis, oil seeps detection etc. A Hyperspectral image contains many spectra, one for each individual point on the sample's surface and in this project the required target on the Hyperspectral image is going to be detected and classified. Hyperspectral remote sensing image classification is a challenging problem because of its high dimensional inputs, many class outputs and limited availability of reference data. Therefore some powerful techniques to improve the accuracy of classification are required. The objective of our project is to reduce the dimensionality of the Hyperspectral image using Principal Component Analysis followed by classification using Neural Network. The project is to be implemented using MATLAB.

1.INTRODUCTION

Recently, a new generation of remote sensing instruments with very high spectral resolution, called imaging spectrometers or Hyperspectral imaging sensors have been developed to uncover subtle material substances that generally cannot be resolved by multispectral sensors. So, Hyperspectral imaging could be used for identifying or detecting a target which is very much smaller and which could be said to be present in sub pixel level. In this way this detection technique could be used in various applications such as special species detection in agriculture, detecting toxic/metal waste in environmental monitoring, rare minerals in geology, drug tracking in law enforcement, diseases in crops, and some other dairy applications.

The use of Hyperspectral images brings in new capabilities along with some difficulties in their processing and analysis. Unlike the widely used multispectral images, Hyperspectral images can be used not only to distinguish different categories of land cover, but also the defining components of each land cover category, such as minerals, and soil and vegetation type. On the other hand, there are also difficulties in processing so many bands. The large amount of data involved with Hyperspectral imagery will, however, dramatically increase processing complexity and time. Effectively reducing the amount of data involved or selecting the relevant bands associated with a particular application from the entire data set becomes a unique, yet primary task for Hyperspectral image analysis. The classification quality may decrease if more image bands are used for the reduction. Feature or subspace selection preprocessing therefore needs to

DOI : 10.5121/ijist.2014.4306

be performed on the data (Campbell 1996). In this paper we use the principal component analysis (PCA) to select the best bands for classification, analyze their contents, and evaluate the correctness of classification obtained by using PCA images.

After extracting the required feature using Principal Component Analysis, classification is needed to be done for detecting the necessary target. For the classification purpose Neural Network is being used.

2. HYPERSPECTRAL IMAGES

Hyperspectral images are those which contain many spectra, one for each individual point on the surface of the sample. These Hyperspectral images have dozens to hundreds of narrow bands. This shows the importance of the Hyperspectral images that the multispectral images have less number of bands.

The range of the Hyperspectral images will be from UV to Long Wave Infrared, but the range of multispectral images will be up to visible region. Hence, vast quantities of data can be obtained from these Hyperspectral images because of the more number of bands which are simultaneously imaged. Since, these images have high dimensionality they could not be classified using traditional classifiers like Maximum Likelihood Classifier.

Two Different Hyperspectral Images are used with the assumption that target is present in one of those images. Two of those images are as shown in the figure below.

Fig 1.1.Band 7 Hyperspectral image.

Fig 1.2. Band 33 Hyperspectral image.

One of the above images has the required target, and by extracting the features of these images, the image with the target is needed to be identified. Thus the images are now ready for preprocessing.

3. PRE-PROCESSING

One of the challenging problems in processing high dimensional data with better spectral and temporal resolution is the computational complexity resulting from processing the vast amount of data volume. This is particularly true for Hyperspectral images containing numerous spectral bands. Preprocessing of Hyperspectral imagery is required both for display and for proper band selection to reduce the data dimensionality and computational complexity. The pre processing process provides some of supports like calibration, atmospheric correction, radiometric correction and data normalization.

The images so taken as inputs are preprocessed to get the output as shown in the figure below.

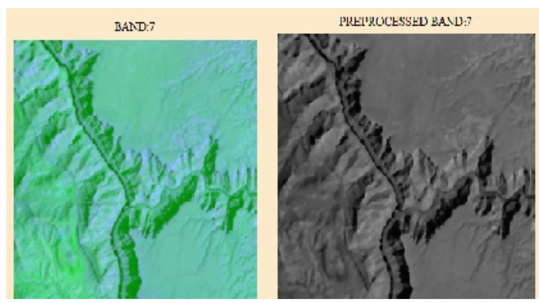

Fig 3.1 a) input image b) preprocessed output

Fig 3.2 a) input image b) preprocessed output

4 .PRINCIPAL COMPONENT ANALYSIS

The principal component analysis is based on the fact that neighboring bands of Hyperspectral images are highly correlated and often convey almost the same information about the object. The analysis is used to transform the original data so to remove the correlation among the bands. In the process, the optimum linear combination of the original bands accounting for the variation of pixel values in an image is identified.

Principal Component Analysis is mainly preferred for feature extraction in Hyperspectral images. This is mainly because the Hyperspectral image is the one which contains more information than the other type of images. So, the dimension of the image will be more in Hyperspectral one than others. And hence dimensionality reduction must be done in order to make the further processing of the image as simple one. Thus for this purpose, we use Principal Component Analysis. This type of feature extraction helps in reducing the dimension, by doing so other process can be considered easier.

The features so extracted from the two Hyperspectral images of 7 bands and 33 bands are tabulated as follows.

Extracted features	
For 7 Bands	**For 33 bands**
0.0162	-0.0029
-0.0289	0.0147
0.0145	0.0283
0.0233	-0.0177
-0.0584	-0.0424
-0.0025	0.0053
-0.0310	-0.0207
-0.0980	0.0389
0.0487	-0.0484
0.0889	-0.0052
-0.0956	0.0135
-0.0146	-0.0093
. . . .	. . . .

Fig.4.1 Table showing the extracted features of band 7 and band 33 hyperspectral images.

5. NEURAL NETWORK

Classification is done with the help of Neural Networks. Neural Network outperforms the other traditional classifiers in many situations. Rigorous evaluation of the classification accuracies shows that the neural network performs better than the other methods and achieves approximately 90% accuracy on test data. This is the main reason for selection of Neural network for the classifying the feature so extracted from the Hyperspectral images.

A significant advantage of Neural Networks verses other types of processing algorithms for Hyperspectral imaging is that they are inherently amenable for parallel implementation. Neural Networks are an appropriate tool for mixed pixel classification due to their capacity to approximate complex non-linear functions.The below block diagram shows the classification by neural network.

Therefore, the classification technique consists of two modules as shown in the block diagram above. They are training module and then testing module. The features of the target are fed in to the training part of the classifier. And then test images are needed to be fed in to the testing module of classification.

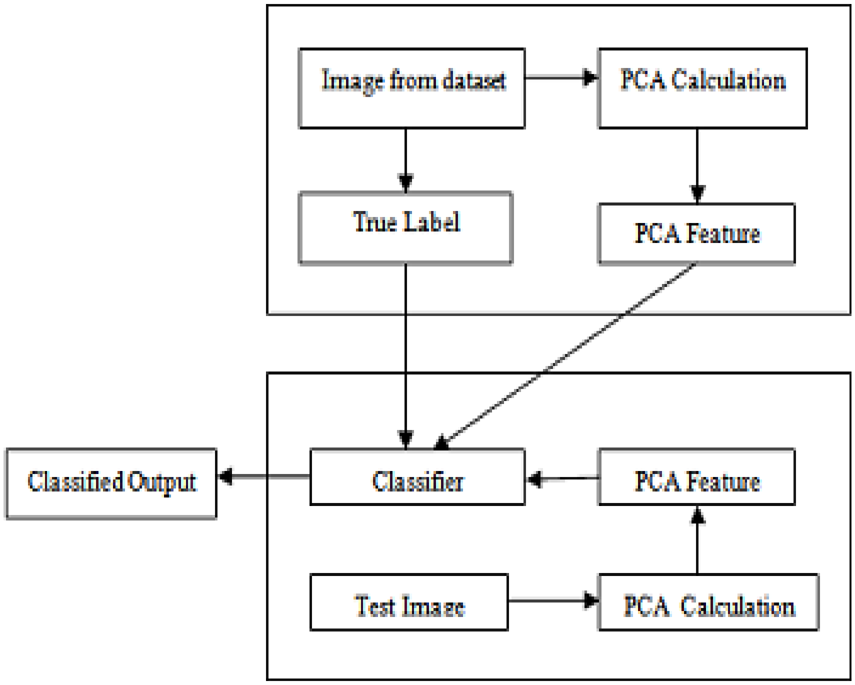

Fig 5.1.Block Diagram showing training and testing modules.

Training Module:

After the PCA calculation of the Hyperspectral images, their features are extracted and labels are assigned according to the presence or absence of the target. These are given to the classifier so present in the Testing module of the Classification.

Testing Module:

Now the PCA calculation for the test image is done. Then the features of that image are extracted and given to the classifier.

The classifier then compares the trained features with the features which are extracted from the test image. With the help of the label so assigned it displays the result as whether the target is present or not.

6. RESULTS AND DISCUSSION

The result of the Principal Component Analysis for both the trained image and the test image is shown below.

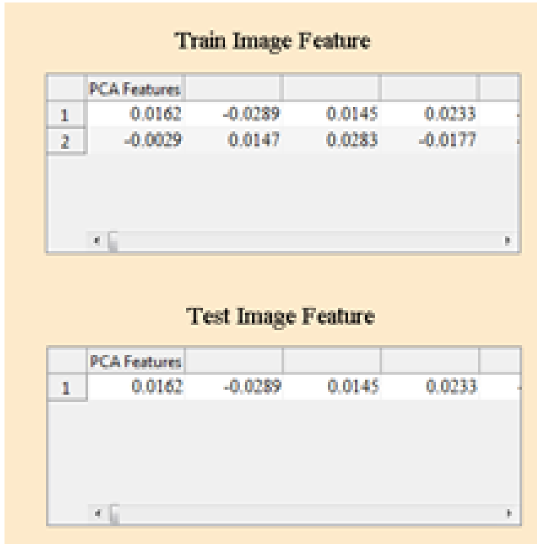

Fig 6.1 Extracted features of trained and tested images.

With the help of the above results, presence or absence of target could be identified. Neural network then classifies it and indicates the presence of target in the image as shown below.

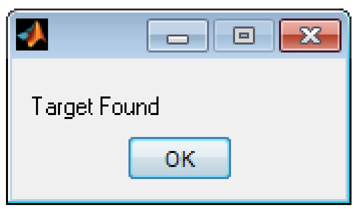

Fig 6.2 Output of Neural network indicating the presence of the target.

And if the target is not found, the neural network classifies and indicates the absence of the target.

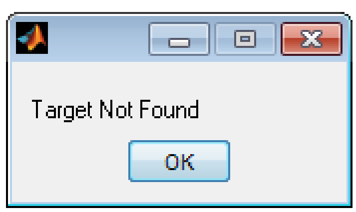

Fig 6.3.Output of Neural network indicating the absence of the target.

We have identified the presence of target using the neural network classifier which is said to be the networks of neurons. Performance of our detection method could be measured by measuring the performance of the neural network so used. And the result so obtained from it shows that our method of detection has high classifier accuracy.

7. CONCLUSION

A novel detection algorithm and our evaluation methodology are described here. This paper reveals that Principal Component Analysis is the useful feature extraction technique for Hyperspectral image classification. High dimensionality images can be easily classified using the given approach.

Neural Network hold good in classifying the sub pixel level stuffs. Thus with the help of this even a very small target can be detected that is, its presence can be known. Hence it can be used in different remote sensing applications like soil classification, crop stress detection, oil seep detection, resources identification, etc.

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