

# Atmospherically Independent Spectral Material Identification Using Parsimonious Features

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## Abstract

*Performing material classification in hyperspectral imagery is a very challenging task, which is complicated by the atmospheric corruption of the material spectra. Current techniques employ expensive atmospheric correction methods which require intensive analyst supervision before the classification is performed. Another problem with current material classification algorithms is that they do not provide a meaningful measure of confidence in their predictions. This limits the utility of the methods because image analysts are not aware of which of the predictions can be trusted. The methods introduced here extend previous work to perform material classification in an atmospherically invariant, automatic manner. The techniques have also been successfully implemented into a conformal prediction framework, which provides a reliable and trusted measure of confidence in the material identification proposed by the processing algorithm.*

Keywords: Spectral, Atmospheric Correction, Material Identification

## Introduction

The motivation for this research was to develop rapid processing techniques to overcome atmospheric effects that are a major impediment to the exploitation of spectral imagery (both multi-spectral and hyperspectral) by Image Analysts. Currently, expensive atmospheric correction methods are employed to uncover the underlying material spectra prior to classification. These methods require a large amount of user supervision and are regarded as an expert discipline. Therefore, techniques which circumvent this correction through processing images in an atmospherically invariant and automatic way present a huge benefit to military operations.

This work extends a previous EMRS DTC project conducted by Waterfall Solutions (WS) [2] which developed a technique for recovering spectral information from an atmospherically corrupted sensor view. The method removed the need for an expensive

and complicated atmospheric correction process by exploiting the constrained nature of the radiation transport functions. Essentially, the technique identified a subspace in these functions which was invariant to the atmospheric effects. The result of this research was an invariant transform which could accurately recover spectral information in a quick and computationally efficient manner.

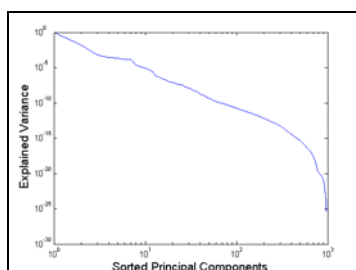
The objective of the work described in this paper was to build upon the success of the atmospheric invariants research in order to perform material identification in an atmospherically invariant way. The investigation resulted in the construction of a new transform which was specifically designed for material classification. This transform is not only invariant to the atmospheric effects, but is also extremely conducive to separating different material types.

The material classification methods that have been developed within this work have

also been implemented within a conformal prediction framework, which provides a well calibrated measure of confidence in the predictions. This enables a better interpretation of the algorithm output, and represents a huge benefit over currently employed techniques which provide little or no confidence estimation.

### Classification Methodology

The objective of this work is to extend the highly successful atmospheric invariants research to material identification. This requires detection of known material spectra in an atmospherically invariant manner. The justification for these invariant techniques can be found through examination of the radiation transport functions. The analysis presented here processed a large number of these functions that were generated using Modtran with a randomisation of the input parameters. Figure 1 illustrates the eigenvalues of the covariance matrix of these functions, which have been sorted in descending order and normalised such that they sum to one. The covariance matrix was constructed from the part of the functions that corresponded to the Near Infra-Red (NIR) band. It can be seen from the figure that only two principal components are required to explain 99% of the variance, highlighting the extremely constrained nature of the functions. It is the fact that these exist in such a constrained space that enables the construction of a transform which can map corrupted spectra into an atmospherically invariant space.



**Figure 1 - Proportion of explained variance of transport function in the NIR band as a function of the number of included Principal Components.**

A number of different methodologies for material identification were examined, but the most successful of these was the novel use of Canonical Correlation Analysis (CCA), which is a statistical technique for identifying correlating vectors in two data sets. This method calculates two sets of vectors for a training set of material spectra which have been corrupted through Modtran-generated atmospheres. CCA chooses the vectors such that the projections of the corrupted and uncorrupted spectra are maximally correlated. The method, therefore, maximises the following expression:

$$\max_{w_x, w_y} \left\{ \frac{w_x^T C_{XY} w_y}{\sqrt{w_x^T C_{XX} w_x w_y^T C_{YY} w_y}} \right\},$$

where  $w_x$  and  $w_y$  are the canonical vectors for the corrupted spectra  $X$  and uncorrupted spectra  $Y$  respectively. The matrices  $C_{XX}$  and  $C_{YY}$  are the covariance matrices, and  $C_{XY}$  is the cross-covariance matrix.

Due to the fact that CCA projects the corrupted spectra into a space where they are maximally correlated with the projections of their true spectral values, the variance that is present in these projections is caused by the variation in material type. Therefore, an automatically gained advantage of this method is that it will project the corrupted material spectra into a space where the different materials are well separated. Therefore, this approach results in a classification methodology which is not only invariant to the type of atmospheric corruption, but also aids the material identification process.

To visualise the effect of projecting the data into the space that is generated through CCA. Two-dimensional (2D) projections of the data are created. Firstly, the dimensionality of the input space can be reduced through the employment of PCA. Projecting the input data onto the first two

principal components, which are the two vectors that account for the most variance in the data, provides the result illustrated in Figure 2. The different colours of the plots represent the different materials. It can be seen that the data is not easily separated in this space, which will make it very difficult for the classification algorithm to accurately predict the correct materials. A much better result is clearly shown in Figure 3, where the data is projected onto the first few canonical vectors. In this space, the material classes are more distinct and represent a much easier task for the classifier. Running a K-Nearest-Neighbour classifier on these data sets results in an error of 0.2612 in the original input space compared to an error of 0.0436 in the CCA reduced space.



**Figure 2 – Input space**



**Figure 3 – CCA space**

### **Conformal Prediction**

Conformal prediction presents a relatively new method for performing learning tasks [3]. The work described here was aided by Universal Predictions Ltd. [4]. Although the technique has been shown to be adaptable to regression and even unsupervised tasks, conformal prediction is originally a

framework for classification problems. Any classifier that learns a mapping from a set of input features to a corresponding class label can be employed within the conformal prediction framework, provided that a real-valued output of the classifier can be obtained. The main benefit of conformal prediction is that it employs a well calibrated measure of confidence for each of the predictions. A confidence parameter is input to the algorithm and the output for each test spectra is a list of possible materials, which are provided with this level of confidence. For example, if a confidence level of 95% is chosen, 5% of classified spectra are expected to be in error. Here, an error is defined as a prediction region that does not contain the correct material. The choice of this confidence parameter depends on the particular application, but higher confidence levels result in larger prediction regions. For the technique to be valid, the only necessary assumption is that the data is independent and identically distributed. This is a subset of other methods such as Bayesian techniques, where the underlying distribution of the data must be assumed.

The methodology behind conformal prediction involves the concept of a non-conformity measure, which characterises the degree to which an example and its corresponding label is non-typical. For nearest neighbour classification, a suitable non-conformity measure can be taken as the distance between the current example and the nearest example of the same class, divided by the distance between the current example and the nearest example of a different class. This is shown below, where  $C$  represents the non-conformity of example  $x_i$  with corresponding label  $y_i$ .

$$C(x_i, y_i) = \frac{\min_j \{ \|x_j - x_i\|_2 : y_j = y_i \}}{\min_j \{ \|x_j - x_i\|_2 : y_j \neq y_i \}}$$

The output of each classified spectra when using conformal prediction is a predictive

region which consists of a set of possible class labels. The algorithm is considered to be in error if the prediction region does not contain the correct label and, therefore, the interpretation of the performance of the technique must consider not just the error rate, but also the size of these regions. Obviously, a method which outputs the full set of classes for each prediction region will never produce an error, but will also never provide any useful information. Consequently, several measures of performance have been derived here to more accurately capture the overall accuracy of the techniques. The score error is one such measure and is calculated through the following function:

$$SE = 1 - \frac{1}{N} \sum_{i: y_i \in P(x_i)} \frac{1}{|P(x_i)|},$$

where  $N$  is the number of spectra being predicted,  $x_i$  is one of these spectra with corresponding material label  $y_i$ , and  $P(x_i)$  is the set of possible classes that has been predicted for  $x_i$ . This function calculates the accuracy through summing the number of prediction regions which contain the correct material but normalises each increment with the size of the region.

Another measure that has been adopted is the region correlation. This measure averages the library spectra that correspond to the materials in the prediction region and calculates the correlation between this average and the true spectra. This can be represented in the following way:

$$RC = \frac{1}{N} \sum_{i=1}^N \text{Corr} \left( z_i, \sum_{j \in P(x_i)} z_j \right),$$

where  $z_i$  is the true spectral signature of material  $y_i$ .

A data set of real material spectra corrupted through Modtran atmospheres was used here to test the classification methods. The data was partitioned into 15,000 examples for training, 2,500 for conformal prediction calibration and 2,500 for testing. The classifier was a K-Nearest-Neighbour (K-nn) with K set to 3. The experiments were conducted on the original input space (input), the input space after dimensionality reduction onto the best 16 Principal Components (PCA), the transformed data using the previous atmospheric invariant transform (Invariant) and the CCA reduced space with 16 canonical vectors (CCA). If too many or too few bands are selected, the accuracy of the technique can be degraded. It was empirically found that 16 bands provided good performance. The results are shown in Table 1 which includes the error rate, average size of the prediction region, and the two derived measures of score error and region correlation.

The table shows how using a K-nn classifier on data which has been transformed using CCA produces the best results. The confidence level was set at 95% and the error rates for all of the methods were within the expected 5% limit. This shows how the conformal prediction framework provides calibrated confidence to the predictions, even when the classification method is poor. Performing the classification on the input space is a

| Learning Method | Error         | Score Error   | Region Size | Region Correlation |
|-----------------|---------------|---------------|-------------|--------------------|
| Input           | <b>0.0180</b> | 0.4350        | 31.44       | 0.8374             |
| PCA             | 0.0208        | 0.4820        | 34.67       | 0.8181             |
| Invariant       | 0.0316        | 0.0728        | 1.91        | 0.9878             |
| CCA             | 0.0420        | <b>0.0447</b> | <b>1.01</b> | <b>0.9904</b>      |

**Table 1 – Results of conformal prediction classification on data after projection into different spaces**

prime example of this, as the error rate is within the expected bound due to an average region size of roughly 31 materials. The score error of over 43% reflects the relatively poor performance of this method. In contrast, transforming the data through the use of CCA produces an error of roughly 4% and a score error that is very similar. This similarity is due to the average region size being slightly over 1, which reflects the superior accuracy when performing the classification in this space.

For practical applications, employing a K-nn algorithm can be computationally expensive because the process stores all of the training examples and then needs to compare each test spectra to all of them. To avoid this, a nearest mean classifier can be used which computes the mean spectra for each class prior to classifying the test data. The classification process is then a simple matter of comparing each test spectra to the mean of each class. Applying this classifier to the same data produces very similar results, as shown in Table 2. Various confidence levels were also used, and the table shows how the resultant error rates from the conformal prediction methodology reflect these different levels. The error of the algorithm is approximately equal to  $1 - \delta$ , where  $\delta$  is the confidence level. The size of the prediction region increases with the confidence level in order to achieve the necessary error rate. This increase in the average region size reduces the overall effectiveness of the method on this data. In practical situations, an appropriate confidence level would need to be chosen to produce acceptable error rates which have prediction regions of a useful size.

These methods have been tested on real data using a classifier based on the Adaptive Cosine Estimator (ACE) [5]. The combination of ACE, the CCA transformation and the conformal prediction framework, provides an accurate method for automatic material identification in real scenarios [1].

### Discussion

The work detailed in this report has built upon the previous atmospheric invariant methodology developed by WS to enable its application to material identification. This invariant method exploits the highly constrained nature of the atmospheric corruption functions to project observed spectra into a space which is invariant to these effects. Analysis of the radiation-transport functions has demonstrated their highly constrained nature, and has also revealed that very few components are required to describe the atmospheric corruption.

Performing material classification in hyperspectral imagery is a very challenging task. A novel application of CCA has been introduced through this project which projects corrupted spectra into a space which is not only invariant to the type of atmospheric corruption, but also aids material classification. The powerful performance of this technique has been illustrated graphically and demonstrated empirically. Another benefit to this new application of CCA is that it reduces the dimensionality of the data and therefore increases the speed of the classification algorithm. Measurements of this speed improvement indicate that on

| Confidence Level | Error  | Score Error | Region Size | Region Correlation |
|------------------|--------|-------------|-------------|--------------------|
| 95%              | 0.0424 | 0.0494      | 1.05        | 0.9889             |
| 97.5%            | 0.0236 | 0.0497      | 1.09        | 0.9891             |
| 99%              | 0.0140 | 0.1641      | 1.47        | 0.9668             |
| 99.5%            | 0.0044 | 0.6597      | 13.7        | 0.8059             |

**Table 2 – Results of nearest-mean classifier on CCA reduced data.**

the data sets investigated in this project (which have over 200 spectral bands) a speed-up of approximately 10-20 times is possible over the other techniques.

A problem with current material classification algorithms is that they do not provide a meaningful measure of confidence in their predictions. This limits the utility of the methods because image analysts are not aware of which of the predictions can be trusted. The work presented here has developed material classification methods within the conformal prediction framework, which incorporates a calibrated confidence measure under very general assumptions. It has been shown that the algorithms output a prediction region with an error that accurately agrees with the pre-set confidence level. This confidence level can be set by the user to provide acceptable classification errors with useful prediction region sizes.

A new, successful and automatic material identification technique has been demonstrated, where the classification accuracy and confidence reliability has been clearly shown. A possible extension to this work is to exploit the automatic nature of the method to enhance current atmospheric correction techniques. This would involve using this automated approach to identify a small set of accurately and confidently classified materials in the scene. These could then be used to automatically perform the atmospheric correction and could potentially provide a better spectral reconstruction of the scene. This methodology could provide very accurate atmospheric correction in a fully automated manner.

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