Outlier and Target Detection in Aerial Hyperspectral Imagery

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I. Introduction

The use of aerial hyperspectral imagery for the purpose of remote sensing is a rapidly growing research area. Currently, targets are generally detected by looking for distinct spectral features of the objects under surveillance. For example, a camouflaged vehicle, deliberately designed to blend into background trees and grass in the visible spectrum, can be revealed using spectral features in the near-infrared spectrum. The received spectral radiance from a remote object depends on the spectral characteristics of the solar illumination and atmospheric attenuation at the location and time concerned. The prevailing atmospheric water vapour content in the ground to air path has a particularly strong effect on measured radiances in the near-infrared region.

This work aims to develop improved target detection methods, using a two-stage approach, firstly by development of a physics-based atmospheric correction algorithm to convert radiance into reflectance hyperspectral image data and secondly by use of improved spectral unmixing techniques. Spectral unmixing is the process of determining the abundance of materials in each pixel of a hyperspectral image. In the linear mixing model the radiance measured at each pixel is assumed to be the linear combination of the radiance of each material present in the pixel. In the non-linear mixing model the radiance measured is assumed to be a weighted sum of the materials within the pixel plus the contribution due to scattering from both the sun to ground path and ground to sensor path.

Here we investigate the use of several spectral unmixing techniques on the raw image data and then a comparison is made between these techniques and the two main unmixing techniques, the Sequential Maximum Angle Convex Cone (SMACC) [1] and Vertex Component Analysis (VCA) [2].

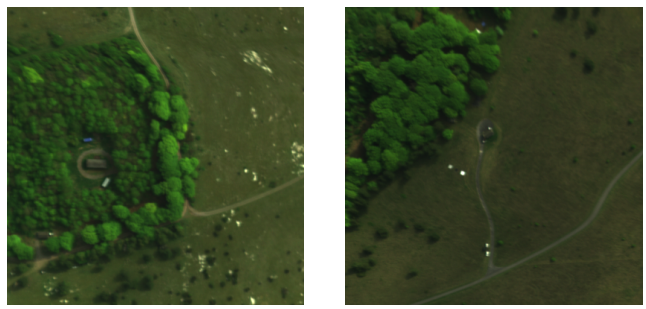
II. Image Acquisition

The imagery used in this paper is all aerial hyperspectral imagery acquired from an aeroplane flying at approximately 0.781km with a mounted hyperspectral sensor. Fig. 1 shows two RGB representations of these images (636nm, 555nm 460nm respectively).

III. Techniques

Outliers are used in hyperspectral imagery to find materials and objects that are spectrally different from the background of the image. Fig. 2 presents a scatter plot created using two bands of the Moll Harris dataset. As the scene is mostly trees and grass which are spectrally similar, there is a large cluster of pixels that all have similar radiance values in each band. The outliers or targets in the scene are the pixels further from the centre of the data. The pixels closer to the centre are more mixed than the further away ones. By determining these it is possible to detect any unusual objects in the image that require further attention.

There are numerous techniques used to find outliers in hyperspectral data. Here we consider two techniques described below to try and improve upon the standard methods.



(a) (b)

Fig. 1: Hyperspectral image taken on 18th May 2014 at 11:29 in Salisbury, Wiltshire (a) Moll Harris site (b) Operation 7 site

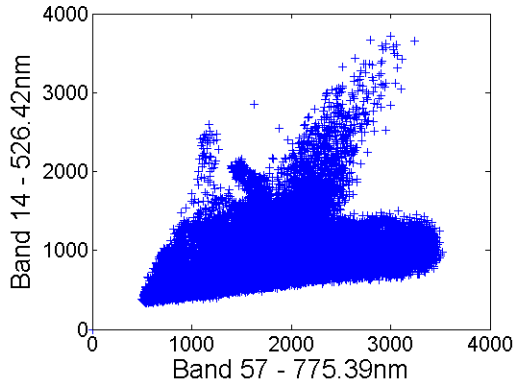


Fig. 2: Scatter plot for Moll Harris dataset using bands 58 and 9 (740nm and 210nm respectively)

A. Mahalanobis Distance

To calculate the Mahalanobis Distance $\mathrm{MD}(x)$ in Eq. 1 for an image pixel vector x requires first calculating a mean pixel vector $\hat{\mu}$ containing the average pixel intensity values for all the bands or wavelengths measured, as well as an estimated covariance matrix of the pixel intensity values for all of the bands using Eq. 2, where N is the number of pixels in the image. Doing this for every pixel vector gives a measure of how far that pixel is from the mean pixel vector. Larger values indicate more extreme pixel vectors.

$$\mathrm{MD}(x) = \sqrt{(x-\hat{\mu})^T \Gamma^{-1} (x-\hat{\mu})} \tag{1}$$

$$\hat{\Gamma} = \frac{1}{N} \sum_{n=1}^{N} (x-\hat{\mu})(x-\hat{\mu})^T \tag{2}$$

B. Percentage Occupancy Hit or Miss Transform

Using a percentage occupancy hit or miss transform (POHMT) [3] to detect outliers in the scatter plot. Fig. 3 shows the four states relating to these outliers.

This was done by first dividing the scatter plot into several small cells each of size 50x50 pixels. A new image was then created which was 1/2500th of the size of the original scatter plot. The number of pixels in every cell of the original image were then counted and the value set in the corresponding pixel of the new image.

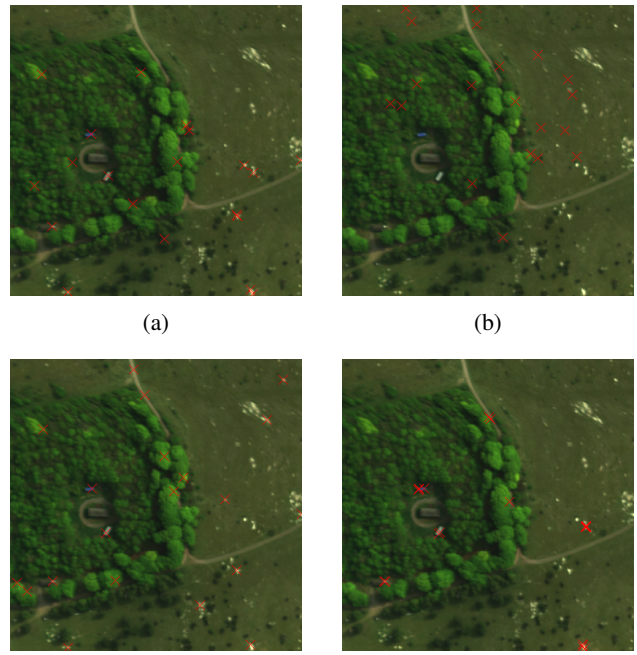
To find the outliers the ratio between the number of pixels in the foreground (blue zone) and the background (red zone) were examined (Fig. 3). This ratio is calculated for every pixel using Eq. 3, where N is the number of pixels in the cell and C_{FG} and C_{BG} are the foreground and backgroudn cells respectively. All values below a certain threshold were then eliminated and the remaining pixels identified as outliers in the data.

Fig. 3: Four states relating to outliers, blue is high, red is low

$$R = \frac{\sum_{i=1}^{N} C_{FG}}{\sum_{i=1}^{N} C_{BG}} \tag{3}$$

IV. Results and Analysis

Fig. 4 presents the outlier locations produced using the two methods detailed above, and also the locations using the standard SMACC and VCA algorithms. Using both the SMACC and VCA algorithms the outliers are detected accurately. They also both detect where each material in the scene is most pure, and for this application this result is not ideal. Using the Mahalanobis distance method there are fewer pixels detected that are simply vegetation and all the objects are still detected. However the high radiance values are also detected as outliers due to the fact that they are spectrally different to the rest of the scene. Finally, using the POHMT there are very few outliers detected but they are all objects in the scene and only one is a vegetation pixel. As with the Mahalanobis technique this also suffers from the problem of detecting high intensity pixels as outliers.



(a) (b) (c) (d)

Fig. 4: Outlier locations identified various techniques (a) SMACC (b) VCA (c) Mahalanobis Distance (d) Percentage Occupancy Hit or Miss Transform

V. Conclusion and Future Work

For this application both techniques are an improvement over the standard methods, however further work to determine a way to eliminate the high intensity pixels being detected as outliers is required.

Further research will also be carried out to develop a technique based on the MODerate resolution atmospheric TRANsmission (MODTRAN) modelling code. By estimating the important atmospheric parameters from data pertaining at the time of measurement, we hope to develop a robust atmospheric correction technique based on these MODTRAN look-up tables. This may simplify the process of spectral unmixing to allow more accurate spectral matching and target detection.

Acknowledgment

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