An Operational Method for Fast Detecting Abnormal Channels in Imaging Spectrometers

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1 Introduction

Hyperspectral remote sensing is of growing interest as a new approach to the examination of solar radiation reflected from the earth’s surface. The ability of an imaging spectrometer to collect data in a large number, typically hundreds, of narrowly defined spectral channels at 10 to 12 bits makes it possible to get hyperspectral data in more detail and with high accuracy and extend the scope of traditional remote sensing.

To make the best use of imaging spectrometer data, the variability or “noise” associated with the sensor’s signal should be measured. The commonly accepted measure to depict data quality is signal-to-noise ratio (SNR). One simple method for estimating the SNR of an image is to find a homogenous area within the image by inspection and then to compute the mean and the standard deviation of the signals in the homogeneous area. The ratio of the mean to the standard deviation gives an estimation of the SNR of the image. This method is referred to as “homogeneous area” method. Another method is called “geostatistical” method, in which a few narrow strips of relatively homogeneous areas are manually selected from an image, and the SNR of the image is estimated from these strips\(^1\). This method is also difficult to automate because of the need to select homogeneous strips. Gao (1993) developed an automatic procedure, in which an image is divided into blocks, and by pooling SNRs of these blocks, the SNR of the image is therefore estimated through averaging the most frequent part of the block SNRs\(^2\). Roger and Aronold’s method for band noise estimation incorporates the data blocking described by Gao so that many estimates are produced\(^3\). In this method,
the spectral and spatial correlations are removed by using multiple linear regression leaving residuals whose mean square value is estimated to be the variance of the band image. The mechanisms underlying in all above methods are common in nature, as they are utilizations of spatial autocorrelations.

Earlier researches show that mutual information analysis can be used to portray spatial correlations between data sets. F. W. Davis and J. Dozier identified land classes by mutual information analysis of vegetation pattern in relation to other mapped environmental variables. Claudio Conese and Fabio Maselli’s tests show the efficiency of mutual information analysis between remotely sensed scenes and ground references related to some theme in selecting optimum bands from TM scenes. Jin applied information theory to analyze the objects and white noise on a digital image. According to the same idea, the present paper uses the measure by way of SNR to portray the autocorrelation characteristic of a data set acquired from an airborne imaging spectrometer. By inspecting a curve which depicts the variation of the measure with channel, abnormal channels are readily detected.

2 Method

Imaging spectrometer produces multispectral images in which adjacent bands are very close in wavelength (about 10 nm or even 5 nm apart) and each band spans a narrow range (also about 10 nm full width, half maximum). The spectral responses of adjacent bands, therefore, overlap significantly. In addition, at this spectral resolution, the solar spectrum, the spectrum of atmospheric attenuation and the spectral reflectance of land cover types change relatively smoothly from one band to the next. In addition to the reasons relating to the sensor’s point spread function, the high spatial resolution from airborne sensors enriches the correlations within a band image. For the reasons above, imaging spectrometer data possess strong within-band spatial correlations as well as strong between-band spectral correlations. These correlations provide accesses to evaluating image quality of different channels. The method proposed in this paper uses a measure called “IHR”, which is derived from mutual information analysis, to describe the spatial correlation within a band and its irregular variation with wavelength to detect abnormal channels. This method has three major aspects:

1) the generation of two subimages from each band image,
2) the computation of IHR for each individual band,
3) the detection of abnormal channels by inspecting the curve of IHR versus channel.

2.1 Generating subimages of a band

For a reason similar to Gao’s 4×4 data blocking, two subimages from a common original image are generated by adopting a sampling strategy. In this paper, for each band image data in a hyperspectral data set, two pairs of sampled images need to be prepared. The first pair are generated by sampling the image data in flight direction, the first part in the pair being formed from lines with odd line number and the second part with even line number. In a similar way, by sampling in scanning direction, the second pair are produced. It should be noted that the image should be sampled in a way to ensure that the two parts in a same pair can respond to each other — the parts in the first pair having same number of lines and the parts in the second pair having same columns. The first parts in the two pairs above constitute one subimage and the second parts in the pairs constitute the other subimage. The two subimages are to be used in the following computation.

2.2 Computing IHR

A remotely sensed image can in fact be considered as a bidimensional variable with discrete levels represented by the grey values. Thus, the relationship among spatially correlated images can be described with measures from information theory.

In mutual information analysis according to information theory, when two variables X and Y with numbers of levels L and M are jointly considered the joint entropy of $H(X, Y)$ is a measure of the
overall information contributed by $X$ and $Y$, and it can be calculated as by

$$H(X, Y) = -\sum_{i=1}^{M} \sum_{j=1}^{M} P(i,j) \ln P(i,j)$$  \hspace{1cm} (1)

where $P(i,j)$ is the proportion of $X$ and $Y$ with levels $i$ and $j$.

The mutual information between the two variables describes the common portion in the overall information shared by $X$ and $Y$, which can be directly computed by

$$I(X, Y) = H(X) + H(Y) - H(X, Y)$$  \hspace{1cm} (2)

where $H(X)$, $H(Y)$ are the entropy of $X$ and $Y$, respectively. They are calculated as

$$H(X) = -\sum_{i=1}^{M} P(i) \ln P(i)$$  \hspace{1cm} (3)

$$H(Y) = -\sum_{j=1}^{M} P(j) \ln P(j)$$  \hspace{1cm} (4)

The conditional entropy of $X$ with given $Y$ is defined as the difference between the entropy of $X$ and the common part which $X$ shares with $Y$, it is

$$H(X/Y) = H(X) - I(X, Y)$$  \hspace{1cm} (5)

The conditional entropy above can be used to measure the information which is contributed by $X$ and is not related with $Y$. If $X$ and $Y$ are probabilistically independent, $I(X, Y) = 0$ and $H(X/Y) = H(X)$, while $X$ is fully associated with $Y$, $I(X, Y) = H(X)$ and $H(X/Y) = 0$.

From the definitions presented above, Eq. (1) to Eq. (5) can be applied to measure the associations among data of a specific scene by using the grey value frequency histograms for corresponding calculation. In two images case, $I(X, Y)$ denotes here the information commonly shared by images $X$ and $Y$, $H(X/Y)$ indicates the information of image $X$ which is independent of image $Y$. Thus, for the two subimages generated in Section 2.1, $I(X, Y)$ can be used as a measure of a specific spatial autocorrelation within a certain band, and $H(X/Y)$ as a measure pertaining to the noise, including coherent sensor noise and random noise as well as the spatial heterogeneity of the scene. Thus, in this way the following equation can be developed:

$$IHR = \frac{I(X, Y)}{H(X/Y)}$$  \hspace{1cm} (6)

For the two subimages, the IHR determines the proportion impartsing information to the proportion imparting the noise as well as scene-specific heterogeneity. With respect to this, the ratio of $I(X, Y)$ and $H(X/Y)$ can serve as an analogue of SNR.

### 2.3 Abnormal channel detecting

As mentioned earlier, data from airborne imaging spectrometers possess both strong spatial correlation within each band and strong spectral correlations between the data in that band and the data in its two adjacent bands. For data from an airborne imaging spectrometer, the curve of IHR versus channel, for which portrays the quality of each band data in a comparative way, should run in a quite smooth way, that is to say, an abrupt trough in the curve implies sharply decreasing in data quality. For the reasons discussed above, such a trough usually indicates where an abnormal channel exists. In this way, simply by inspecting the curve of IHR versus channel, abnormal channels are readily detected.

### 3 Experiments

Experiments aimed at verifying the validity of the presently proposed method have been done. All the software involved in the experiments of this paper are developed under the environment of IDL. In these experiments, the method was applied to one PHI data set and one Hymap data set.

#### 3.1 PHI data set

The PHI data set was sensed in 80 visible and near-infrared wavebands with spectral resolution less than 5 nanometers. Fig. 1 shows the curve of

![Distribution of $I(X, Y)$ to $H(X/Y)$ ratio](image)
i-HR versus channel, in this plot, there is a sharp deep trough at channel A compared with its neighboring channels, which, according to what have been introduced in Section 2.3, should predict a quick decrease in data quality. This prediction is indeed verified with a visual examination. The single band images from channel A, its former neighboring channel and latter neighboring channel are shown in Fig. 2, which are noted asFig. 2(b), 2(a) and 2(c), respectively. Actually, the IHR value of the two subimages generated from Fig. 2(b) is 0.2661, while the values are 0.339 and 0.335 for the two pairs of subimages respectively generated from Fig. 2(a) and 2(c).

3.2 Hymap data sets

Hymap has been developed in Australia and now deployed for commercial operations around the world. With almost contiguous spectral coverage across the wavelength interval 0.45 μm to 2.5 μm, the Hymap data set used in the experiment is in 124 spectral channels[8]. The curve of IHR versus channel is shown in Fig. 3. Similar to what has been described in Section 3.1, a sharp deep trough at A predicts an abnormal channel. Visual examinations can readily verify the prediction - the image noted as Fig. 4(a) is from channel A, while Fig. 4(b) is an image from one of its two adjacent channels. Also, the trough at B imparts another instance of this phenomenon. Fig. 4(c) and 4(d) are the images from B and one of its two adjacent channels, respectively. The IHR values for the two pairs of subimages generated from Fig. 4(a) and 4(b) are respectively 0.007 and 0.211. For the two pairs of subimages respectively generated from Fig. 4(c) and Fig. 4(d), the value pair are 0.105 and 0.255.

4 Discussion

The proposed predictor is designed in this paper on the basis of comparison among neighboring channels in an airborne imaging spectrometer. It is called “an analogue of signal-to-noise ratio” and it is designed not to be aimed at the real measure of...
signal-to-noise ratio of a sensor. Therefore, the measurement value cannot be used for a quantitative comparison in terms of signal-to-noise ratio. One may think that the $H(X/Y)$ part in the ratio computing also conveys the fluctuations attributable to spatial variations with spectral wavelength in the scene. This is true. Nevertheless, it does not affect its validity, as initially designed, for purpose of detecting abnormal channels in an airborne imaging spectrometer. For the reasons discussed in Section 2.3, the spatial variations with spectral wavelength can only cause smooth and progressive changes in the curve. As is shown in Fig. 1 and Fig. 3, the smooth and progressive fluctuations in the curves are significantly different from those abrupt deep troughs.

The image data used in the experiments are all in DN form. The method proposed in this paper can be also suitable for radiance images. As affine transformations do not change the correlation structure of the data, the method will work equally well on reflectance data generated by that type of atmospheric correction procedure.

5 Conclusion

A non-conventional utilization of information analysis is put forward for establishing a procedure to detect abnormal channels in an airborne imaging spectrometer. The predictor used is simple and easy to implement. Just by inspecting the finally obtained curve, instead of visually examining each band image in an image data set as in conventional method, abnormal channels in an airborne imaging spectrometer can be readily determined, so it is much automated and effectively obviates the hard labor burden. As is seen in the experiments, this method is straightforward compared with Gao’s, Roger and Aronold’s methods. Because it requires no knowledge relevant to the distribution of the imaged scene, this method is much more automated and operational than “homogeneous area” method and “geostatistical” method. Given the mechanism underlying in the procedure, it could be applied to remotely sensed data from other airborne hyperspectral sensors.

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