SPECTRAL SUPER RESOLUTION FOR EXTRACTION OF VEGETATION INDICES FROM MULTISPECTRAL SATELLITE IMAGERY

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KEY WORDS: multispectral, spectral resolution, sensor, vegetation indices, satellite imagery

Abstract: This research aims to develop a method to enhance the spectral details of multispectral satellite imagery. We take into account of the physical model of sensor response function and present a method to reconstruct the reflective spectrum at the front end of sensor in an iterative way, which is synonymous to an ideal spectrum and continuous spectral curve of objects with little influence from sensor. Accordingly detailed spectral data can be generated from a re-sampling process on the generated spectrum curve. Comparing with the conventional methods, our method has an advantage to recover the reflective spectrum with a faithful preservation of spectral signatures of objects and no additional information is required except of sensor response function which is normally available as metadata. Through applying to extract vegetation indices, we demonstrated that our method opens a new way to discover the spectral details from multiple-spectral data, which is only possible in using hyper spectral data at present.

1. INTRODUCTION

Satellite imagery has become one of important data sources for monitoring Earth environment and is being introduced in various application fields. Besides the spatial and temporal details, there are also increasing demands for discovering spectral information from remotely sensed imagery. Among a large number of researches, enhancement of imagery spectral details has been recognized as an efficient way to improve the potential capacity of imaging system.

Most of the current commercial satellites provide only multiple spectral (MS) bands (4-8 bands) image data. Because the band width is relatively large (up to several hundred nm), it is normally difficult to retrieve the detailed spectral features, which could be very significant for some applications, such as vegetation species classification, crop growth status identification, cloak detection etc. On the other hand, hyper spectral (HS) imagery, which contains several hundred narrow bands (dozens nm of wave width) has been recognized very useful for achieving highly accurate classification, unfortunately, due to the present manufacture level of hyper spectral sensor, acquisition of hyper spectral imagery is limited to a close or up to a middle range, which results in the most current hyper spectral imagery being only acquired from aerial platform or directly taken on the ground and therefore the data cost is relatively high. Though satellite hyper spectral imaging system is emerging, it would still take a time to be practically available.

To fill the gap between the demands and data cost, a lot of efforts have been paid to enhance the spectral details of current multiple spectral satellite imagery. Among them, spectral unmixing [1] technique is very popular, the basic idea is quite straight, that is for a given pixel with its spectral curve, it can be divided into an optimal combination of its compounds, which are termed as end members, the processing is kind of reverse process of mixing these end members into a mixed spectral curve, so called spectral unmixing. The required inputs for spectral unmixing is the number and the spectral signature of end members in each pixel, which is normally unknown and actually the interest of spectral analysis in most cases, this leads to a question of “chicken and egg”. On the other hand, other researches tackle this problem using various methods. The term of ‘super resolution spectral’ has been presented in [2][3][4][5][6]. Though the methods to generate super resolution spectral data are quite different, they share a common idea that is to calculate the unknown spectral intensity values through a spectral interpolation scheme, which is synonymous with the popular super resolution technique in spatial domain.

In order to discover as much as detailed spectral features from the current commercial high resolution satellite imagery, which is playing one of central roles in Earth observation data industry, we proposed a novel method to generate the super resolution spectral data from the normal multiple spectral image data by considering the physical characteristics of sensor.

This paper is organized as: following a brief background introduction as above, we discuss the characteristics of spectral imaging system which later leads to our proposal of spectral resolution enhancement in the next section, then our method to generate super spectral resolution is explained in the third section followed by some experiments. Finally a summary is given to conclude the paper.

2. SPECTRAL IMAGING

It is an important technology to acquire spectral information for remote sensing to monitor the environment of Earth. For each pixel of a spectral image we have a sample of the reflective electromagnetic spectra of the object contained in the field of view of the sensor as illustrated in Figure 1. The high spectral resolution of spectral imagery gives us the capability to perform spectrometric analysis of the measured spectral signature.

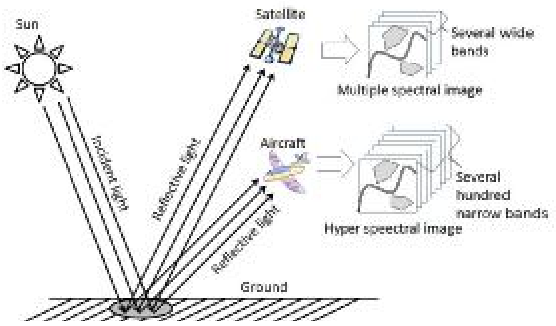

Figure 1: Spectral imaging system of remote sensing

There are two categories in spectral imagery, named Multiple Spectral (MS) and Hyper Spectral (HS) imagery according to the number of their bands and wavelength of each band. Equivalent to the concept of resolution in spatial domain, the wavelength of band is often referred as the spectral resolution, which indicates how details in spectral features can be distinguished from each band. Hyper Spectral image data normally contains several hundred narrow bands whose wavelength of each band is about dozens nm, meanwhile multiple spectral image data has a few (below 10) wide bands and their band wavelength is up to several hundred nm. As illustrated in Figure 2, the high spectral resolution of hyper spectral image offers a high potential to depict the spectral signatures of object.

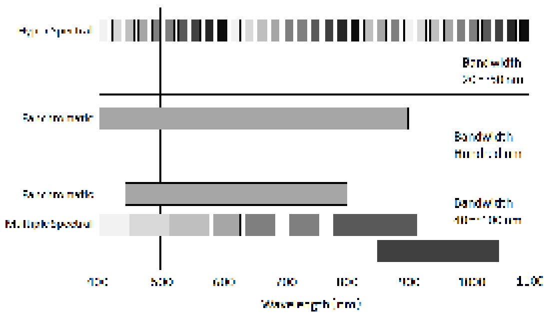

Figure 2: Hyper spectral and multiple spectral image data

Due to the present manufacture level of hyper spectral sensor, acquisition of hyper spectral imagery is limited to a close or up to a middle range, which results in the most current hyper spectral imagery being only acquired from aerial platform or directly taken on the ground and therefore the data cost is relatively high. Though satellite hyper spectral imaging system is emerging, it would still take a time to be practically available.

Besides of the advance of sensor technology, a number of techniques have been developed to enhance the details of remote sensing imagery. The main stream has been focusing on enhancing the spatial resolution through an interpolation scheme taking into account of spatial consistence, so called super resolution as illustrated in Figure 3 (left). Though another stream of methods is drawn little attention, it is very significant to enhance the image details in terms of spectral resolution as illustrated in Figure 3 (right).

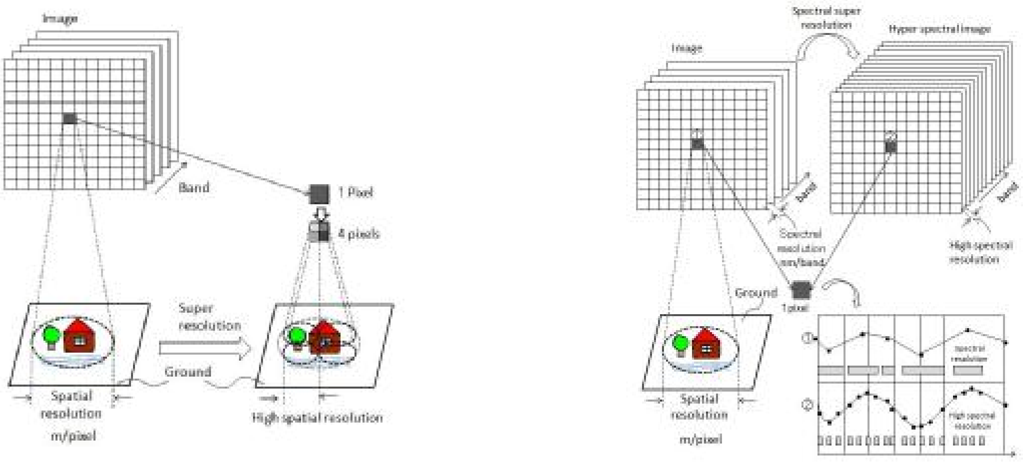

Figure 3: Super resolution in spatial domain (left) and spectral domain (right)

It is very straight to regard a pixel as a mixture of its possible constituent elements. Once the spectrum of elements is known, we always can find an optimal combination of its fractions to best fit the total spectrum of the pixel. This technique is called spectral unmixing, a very popular method to decompose a spectrum into detailed ones. The required inputs for spectral unmixing is the number and the spectrum of end members in each pixel, which is normally unknown and actually the interest of spectral analysis in most cases. To generate hyper spectral image data from multiple spectral data, the conventional methods are neither sufficiently reliable nor operational. To this end, we present an effective method to restore well the reflective spectral curve of objects by integration of physical features of sensor and further provide a great potential for spectral feature analysis.

3. GENERATION OF SPECTRAL SUPER RESOLUTION

The current methods to enhance the spectral information are mainly focused on image and its attributes and this leads to the influence of sensor being little considered and mostly ignored. As illustrated in Figure 4, the incident light R contains the actual reflective spectral features of objects which is synonymous to an ideal and continuous spectrum, once R passes through sensor, sensor influences are added and discrete spectral image data is generated by a sampling process. In order to mitigate sensor influences, it is very necessary to take into account sensor's physical characteristics. The sensor's physical spectral response characteristics are usually depicted by a relative spectral response function (SRF) for each band, which is defined as the ratio of output signal to incident flux as a function of wavelength, normalized to peak value of unity.

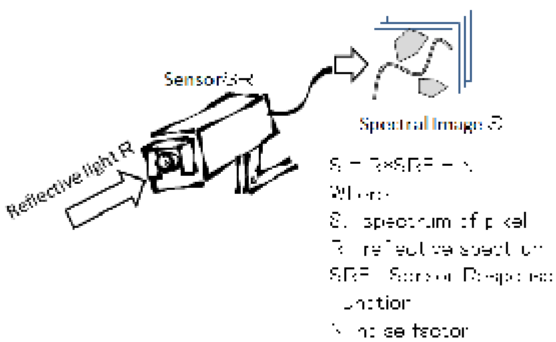

Figure 4: Sensor influence and sensor response function

The process of conversion of incident light intensity into digital number of pixel value by sensor is very complicated, which consists of light being attenuated by the lens, dispersed by the spectrometer, responded by the detector to generate electrons, and finally output by the readout electronics. Accordingly SRF is introduced to generalize the spectral influence of sensor, and can be simplified as equation (1):

$$S_i = \int R_i(r) SRF_i(r) d(r) + N_i \tag{1}$$

Where S_i is the spectral value of ith band. $R_i(r)$ is the continuous spectral curve at the front of sensor entrance corresponding to the spatial position of the specific pixel. $SRF_i(r)$ is the sensor response function of wavelength. N_i is the noise factor. In equation (1), S_i corresponds to multiple spectral image data and its values are discrete. $SRF_i(r)$ is usually available as the metadata. N_i can be regarded as a constant value. Then the question becomes how to solve $R_i(r)$ with known S_i and given $SRF_i(r)$. However, the SRFs at discrete wavelengths are not identical, and the current deconvolution methods for a unique continuously moving filter are not adequate to solve the problem. Based on the fact that if (1) is applied to a continuous spectrum and produces a discrete spectrum which equals to the spectral value of image, the input continuous spectrum is most likely to be the actual incident spectrum. Therefore we propose a method in an iterative scheme to recover the reflective spectrum at-sensor as illustrated in Figure 5.

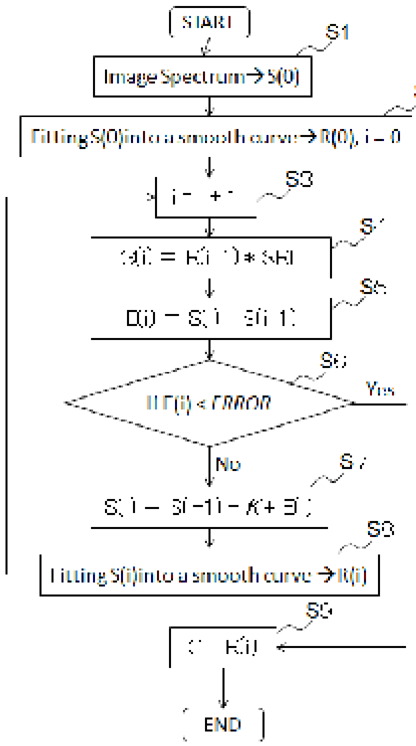

Figure 5: Workflow of spectral super resolution generation

Our method starts with a spectral curve fitting (step S1). Because the actual incident spectrum is continuous, we apply cubic spline fitting algorithm to generate a smooth curve passing through every spectral data points, and use this spectral curve as an initial incident spectral curve R(0) (step S2). Then we apply equation (1) to calculate the spectral value S(1) output from sensor with the given SRF (step S4). There is a difference between previous spectral value S0 and calculated one S1, called spectral error E(1) (step S5). We compare error E(1) with a predefined error threshold ERROR (step S6), if E(1) is smaller than ERROR, the currently generated smooth incident spectral curve R(0) can be used to calculate image spectral values S(1) with the given SRF (step S9), and it actually solve our problem and results in a smooth incident spectral curve which is very close to the actual one. On the other hand, if E(1) is bigger than ERROR at (step 6), we move each calculated spectral value S(1) towards their corresponding actual value to get new spectral value S(2), where K is a parameter to control approaching speed (step 7). Then we can again fitting these new spectral values into a new smooth spectral curve and repeat step S3 to S8 until we finally find a smooth spectral curve which meets our requirements to produce the original image spectral values. The above process is also illustrated in Figure 6 (left).

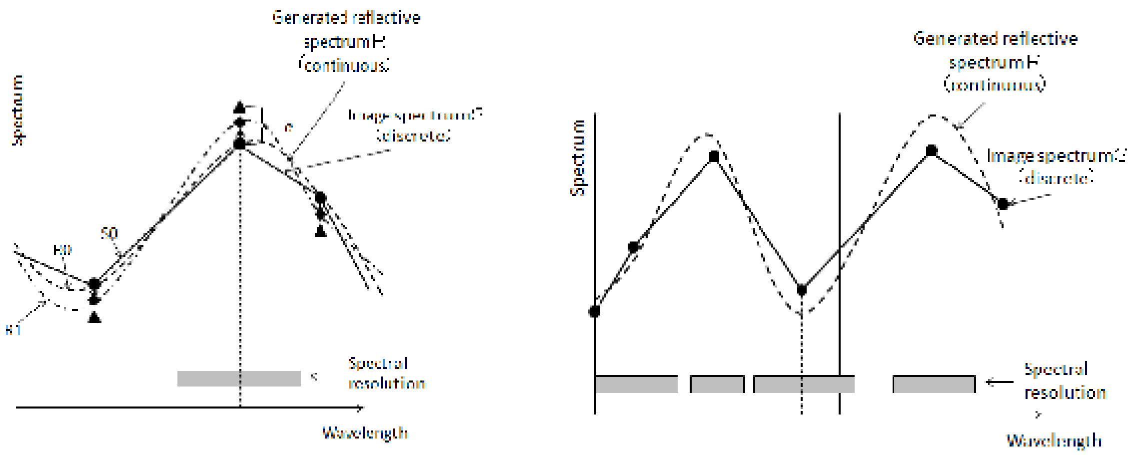

Figure 6: Iterative method to solve smooth incident spectral curve (left); Reconstruction of smooth incident spectral curve from discrete spectral value (right).

Once the smooth incident spectral curve is recovered, the rich spectral features can be retrieved. As illustrated in Figure 6 (right), the spectral value at any wavelength is therefore available hence hyper spectral data with a large number of narrow bands can be simply generated through a re-sampling process.

Comparing with the conventional methods, our method has an advantage to recover the reflective spectrum with a best preservation of spectral features of objects. No additional information is required except of sensor response function which is normally known. Therefore our method is either reliable or operational, and opens a new way to discover the spectral features from multiple-spectral data, which is only possible in using hyper spectral data at present.

4. EXPERIMENT

To validate our proposed methods and assess the performance, we conducted an experiment using commercial high resolution satellite image, and experimental results are shown as follows:

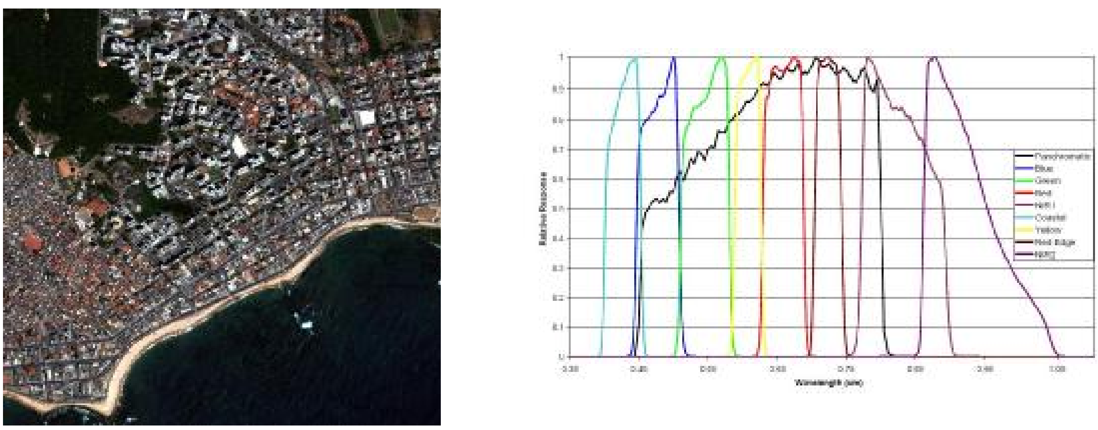

Figure 7: Worldview-2 satellite multiple spectral image (left), and its Sensor response function (SRF) (right). The copyright belongs to DigitalGlobeⒸ

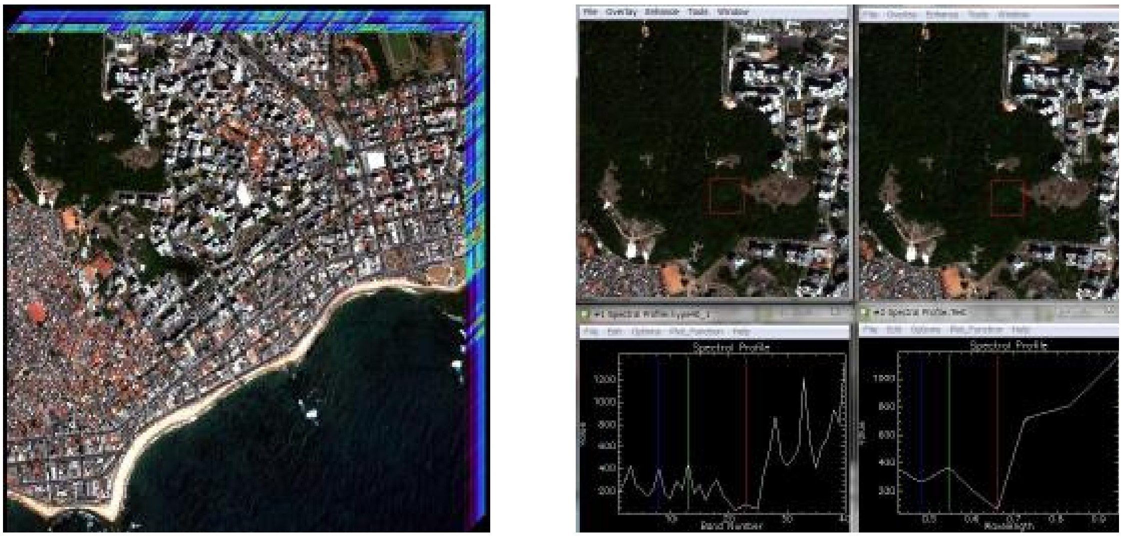

Figure 8: Left is the generated hype spectral image data by our method using Worldview-2 multiple spectral data. The number of band is 40; Right is the comparison of spectral signatures between generated hyper spectrum (left column) and the original multiple spectrum (right column). Detailed spectral features are enhanced when the spectral resolution is increased.

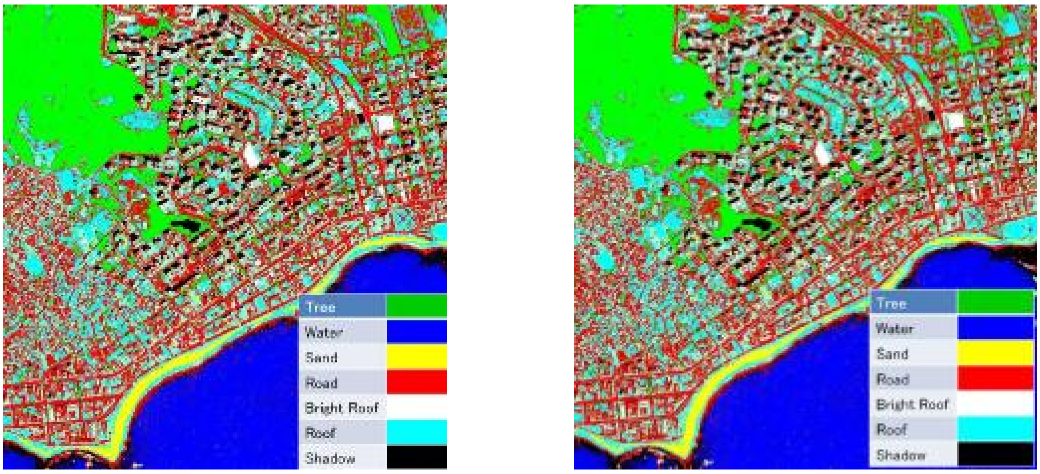

Figure 9: Classification of Worldview-2 image and the accuracy is about 79.4% (left); Classification result of generated hyper spectral image data, and the accuracy is about 89.4%, comparing the above result, the accuracy is improved up to 9.6% (right).

5. CONCLUSIONS

Information discovery from satellite imagery is a great challenge and also a driving force behind the commercial success in Earth environment observation industry. To meet the increasing demands for abundance of information from various disciplines, a large number of techniques in enhancement of spatial and temporal details have been developed in last decades. Meanwhile the advance of hyper spectral sensor technology greatly expands the potentials of imaging systems, brings a considerable amount of hidden spectral information visible. However due to the present manufacture level of hyper spectral sensor, acquisition of hyper spectral imagery is limited to a close or up to a middle range, which makes the most current hyper spectral imagery to be only acquired from aerial platform or directly taken on the ground and therefore the data cost is relatively expensive. Though satellite hyper spectral imaging system is emerging, it would still take a time to be practically available. Thus the high cost of hyper spectral data currently forms a barrier for its wide applications. Rather than hardware improvement, software solution has been somehow drawn less attention.

The conventional methods to enhance the spectral information are mainly focused on image and its attributes and this leads to the influences of sensor being little considered and mostly ignored. Based on the physical model of sensor, our method finds an iterative way to recover the reflective spectrum at the front of sensor, which is synonymous to the ideal spectrum and is continuous spectral curve with no influence coming from sensor. Accordingly hyper spectral data can be generated from a re-sampling process on the generated ideal spectrum curve. Comparing with the conventional methods, our method has an advantage to recover the reflective spectrum with a best preservation of spectral features of objects. No additional information is required except of sensor response function which is normally known. Therefore our method is either reliable or operational, and opens a new way to discover the spectral features from multiple-spectral data, which is only possible in using hyper spectral data at present. We have accomplished the following research objectives: (1) an iterative spectral interpolation method is presented. Because of integration of sensor response function, our method is able to recover the spectral curve of object in a more reliable way; (2) a method to generate spectral super resolution data from multiple spectral data is developed. Not only spectral features are well preserved but also the details of spectral information are precisely enhanced, the identification capacity and classification potential of generated hyper spectral data are greatly improved; (3) our method is able to largely increase the cost-performance ratio of current satellite multiple spectral imagery through a faithful simulation of hyper spectral image data, and also reveals great potentials of satellite imagery in various disciplines.

Future work will focus on evaluating the spectral quality in generated hyper spectral bands and as well the spatial consistence of spectral interpolation. One consideration is to combine the both super resolution techniques in spatial and spectral domains, and to generate a sort of super detailed satellite imagery.

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