Vegetation index derived from the AVIRIS hyper-spectral airborne imagery

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Abstract

The objective of this paper is the description of the development and the validation, using airborne hyper-spectral imagery data, of a non-conventional technique for the vegetation information extraction. The proposed approach namely the universal pattern decomposition method (UPDM) is tailored for hyper-spectral imagery analysis, which can be explained using two analysis methods: spectral mixing analysis and multivariate analysis. For the former, the UPDM expresses the spectrum of each pixel as the linear sum of three fixed, standard spectral patterns (i.e., the patterns of water, vegetation, and soil); each coefficient represents the ratio of spectral patterns of three components. If we think of the UPDM as multivariate analysis, standard patterns are interpreted as an oblique coordinate system, and coefficients are thought of as the coordinates of a pixel's reflectance. The later explanation is much more comprehensible than the former for the reason of additional supplementary pattern presence when necessary. This paper validates the UPDM using AVIRIS airborne imagery, and the results provide an expected assumption.

Introduction

Vegetation indices (VIs) derived from the satellite remotely sensed imagery are one of the primary sources of information for operational monitoring of the Earth's vegetative cover. VIs have the property of being sensitive to a variety of biophysical vegetation canopy parameters, such as leaf area index, fraction vegetation cover, leaf angle distribution and leaf chlorophyll concentration [1]. Most of them are called broadband VIs because they are based on algebraic combinations of reflectance in the red, R, and that in the near infrared, NIR, spectral bands [2]. The broadband indices use average spectral information over broad bandwidths, resulting in loss of critical information available in specific narrow bands [3]. In addition, the broadband indices are known to be heavily affected by soil background at low vegetation cover [4]. Hyperspectral sensors measure reflectance in a large number of narrow wavebands, generally with bandwidths of less than 10 nm. With these narrow bands, reflectance and absorption features related to specific crop physical and chemical characteristics can be detected (Strachan, *et al*., 2002). With many airborne imaging spectrometer systems in use today and the rise of spaceborne hyperspectral sensors, better understanding of this type of image data is increasingly needed [6]. VIs derived from the R and NIR bands is unsuitable for hyperspectral data (i.e. AVIRIS) analysis.

The universal pattern decomposition method (UPDM) is a sensor-independent method that is tailored for satellite data analysis [7] [8]. The UPDM can be explained using two analysis methods: spectral mixing analysis and multivariate analysis. For the former, the UPDM expresses the spectrum of each pixel as the linear sum of three fixed, standard spectral patterns (i.e., the patterns of water, vegetation, and soil); each coefficient represents the ratio of spectral patterns of three components. If we think of the UPDM as multivariate analysis, standard patterns are interpreted as an oblique coordinate system, and coefficients are thought of as the coordinates of a pixel's reflectance. The later explanation is much more comprehensible than the former for the reason of additional supplementary pattern presence when necessary. This method has been successfully applied to simulated data with wavelengths observed by Landsat/ETM+, Terra/MODIS, ADEOS-II/GLI and 92 bands-CONTINUE sensors[7], and validated using MODIS and ETM+ satellite data from over the Three Gorges region in China[9]. This paper validates the UPDM using AVIRIS airborne imagery, and the results provide an expected assumption.

Methodology

The Universal Pattern Decomposition Method

The UPDM decomposes reflectance values at each pixel into a linear sum of standard spectral patterns for water, vegetation, soil and any supplemental patterns using the following formula [9] [10]:

$$R_i \to C_w \cdot P_{iw} + C_v \cdot P_{iv} + C_s \cdot P_{is} \vdots + C_4 \cdot P_{i4} \qquad (1)$$

where R_i is the reflectance of band i measured on the ground (or by satellite sensor), C_{w}, C_{v} and C_{s} are the respective decomposition coefficients, C_4 represents supplemental coefficients, and P_{iw}, P_{iv}, and P_{is} are the standard spectral patterns of water, vegetation and soil for some typical sensor, which is intercepted from the same standard pattern normalized in the same wave region of 350nm to 2500nm for any sensor, which is thus respect to the properties of each sensor. P_{i4} is the supplementary standard pattern for i bands and is an optional component that is also controlled by the purpose of the study. For example, for MODIS and ETM+, P_{iw}, P_{iv}, P_{is}, and P_{i4} are different as the description in the following section, but they are all intercepted from the same normalized standard spectral pattern, namely, sensor-independent standard spectral pattern. In this case, a yellow-leaf spectrum is used, but the supplemental pattern is not fixed. Rather, it depends on the study purpose.

Equation (1) can be expressed using matrix notation as follows:

$$\mathbf{R} = \mathbf{PC} + \mathbf{r} \qquad (2)$$

or

$$\begin{pmatrix} R_1 \\ R_2 \\ \vdots \\ R_n \end{pmatrix} = \begin{pmatrix} P_{1w} & P_{1v} & P_{1s} & P_{14} \\ P_{2w} & P_{2v} & P_{2s} & P_{24} \\ \vdots & \vdots & \vdots & \vdots \\ P_{nw} & P_{nv} & P_{ns} & P_{n4} \end{pmatrix} \cdot \begin{pmatrix} C_w \\ C_v \\ C_s \\ C_4 \end{pmatrix} + \begin{pmatrix} r_1 \\ r_2 \\ \vdots \\ r_n \end{pmatrix} \tag{3}$$

where $\mathbf{R} = [R_1, R_2, \ldots, R_n]^T$ is the column vector of observations, n is the number of spectral bands; $\mathbf{P} = [\mathbf{P_w}, \mathbf{P_v}, \mathbf{P_s}, \mathbf{P_4}]$ is the $n \times 4$ matrix of which the row vector is the standard spectral pattern for band number n, $\mathbf{C} = [C_w, C_v, C_s, C_4]^T$ is the column vector of UPDM coefficients and $\mathbf{r}$ is the residual column vector for band i. Inverting (2) and minimizing the sum-of-squared-error criterion function yields the unique solution of $\mathbf{C}$ is

$$\mathbf{C} = (\mathbf{P}^T\mathbf{P})^{-1}\mathbf{P}^T\mathbf{R} \tag{4}$$

where $\mathbf{R}$ is a vector known from satellite data, and $\mathbf{P}$ is a standard spectral pattern matrix as described above. The spectral pattern matrix is derived from normalized standard spectral patterns of water, vegetation, soil, and supplementary data, which in this case is yellow leaf [9].

Vegetation Index Computation

We have developed a new vegetation index that was based on a universal pattern decomposition method (VIUPD) [11]. The new vegetation index was normalized by total reflectance or total brightness to minimize shadow effects and obtain stable values. The index is a function of the linear combination of the pattern decomposition coefficients. The formula is given as follows:

$$VIUPD = \frac{(C_v - a \times C_s - C_4)}{C_w + C_v + C_s} \tag{5}$$

where ($C_w + C_v + C_s$) represents the sum of total reflectance, even an supplementary pattern is included, since the integrated value of $\int r_4(\lambda)d\lambda$ equal zero [11], and a is the coefficient of standard soil pattern coefficients. The C_s term in the numerator is a correction term for dead vegetation, because the spectral pattern for dead vegetation contains a small portion of the vegetation pattern. We determined parameter a so that the average VIUPD value for dead vegetation equals zero. For standard vegetation, the VIUPD value equals 1. In this case, the value of a is 0.10.

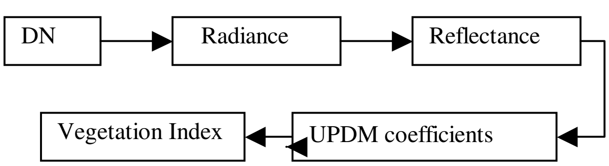

***Figure 1**. Flowchart of vegetation index computation*

Figure 1 schematically shows the step of vegetation index computation. Remotely sensed digital number (DN) was firstly converted to radiance value, and then by using formula (4) and (5), vegetation index imagery was obtained.

In this study, we used the same water, vegetation, and soil standard spectral patterns. Figure 2 shows the normalized standard patterns of soil, water, vegetation, and the supplementary pattern. In the UPDM, however, we converted an uninterrupted spectral wavelength range from 350 to 2,500 nm, excluding regions of strong atmospheric absorption. Therefore, the total number of bands equaled 1,260. When the UPDM approach applies on AVIRIS data, we intercept the normalized standard patterns values correspond to AVIRIS sensor band center position, the matrix $\mathbf{P}$ then are obtained. Since some of AVIRIS band have zero signal values, the finally band number for AVIRIS is 123, thus $\mathbf{P} = [\mathbf{P_w}, \mathbf{P_v}, \mathbf{P_s}, \mathbf{P_4}]$ is the 123×4 matrix vector.

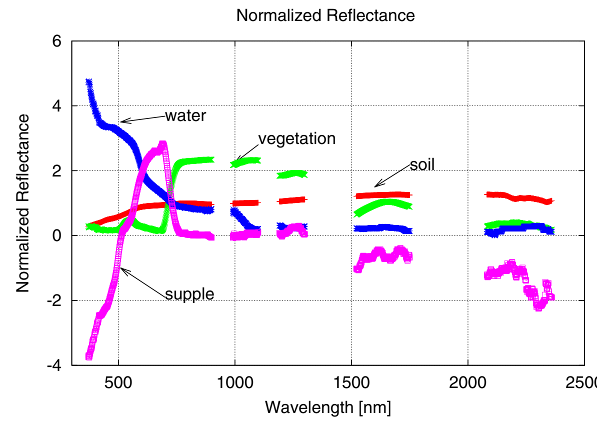

***Figure 2**. Normalized standard patterns of soil, water, vegetation, and the supplementary pattern. This figure shows the normalized values of the standard spectral patterns of water, vegetation, and soil used for vegetation index computation; the supplementary standard pattern represents a yellow leaf.*

Data Used in This Test

AVIRIS is an acronym for the Airborne Visible InfraRed Imaging Spectrometer. The AVIRIS instrument contains 224 different detectors, each with a wavelength sensitive range (also known as spectral bandwidth) of approximately 10 nanometers, allowing it to cover the entire range between 380 nm and 2500 nm [12].The AVIRIS Standard Data Products was downloaded from Jet Propulsion Laboratory website [12]. This data was acquired over the Moffett Field, with vegetation, urban and water included. The measurements data (DN) was converted to ground reflectance data with proper calibration and correction for atmospheric effects. Figure 3 shows the selected region of AVIRIS reflectance imagery.

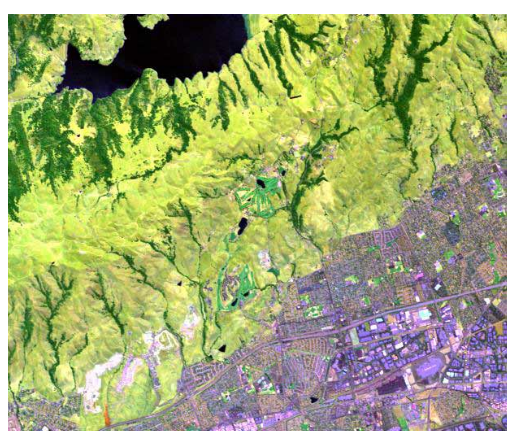

***Figure 3**. Original AVIRIS reflectance imagery*

Results and conclusions

In this study, three vegetation indices (VIUPD, NDVI, and EVI) imagery were computed from AVIRIS imagery. VIUPD images from AVIRIS shows more detailed information than NDVI and EVI images. Figure 4 shows the VIUPD vegetation index imagery.

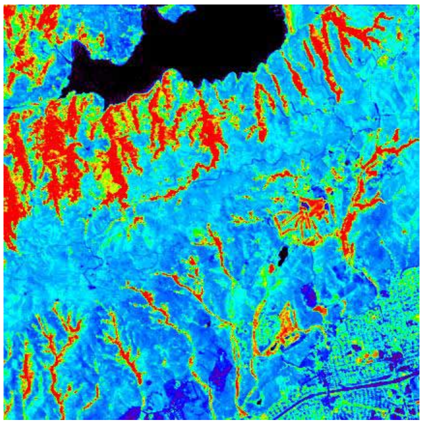

***Figure 4**. Vegetation index VIUPD imagery derived from AVIRIS data*

The vegetation index, based on the universal pattern decomposition index (VIUPD), reflects the linear sum of the four pattern decomposition coefficients. The VIUPD reflected vegetation concentrations, the amount of CO2 absorption, and the degree of terrestrial vegetation vigor more sensitively than did the NDVI and EVI, and was especially sensitive to CO2 absorption [11]. Two or three reflectance bands are used to calculate EVI and NDVI, while the VIUPD use multi-spectral satellite- and ground-measured reflectance data. The VIUPD is computed using four UPDM coefficients, that is, the VIUPD is a linear function of C_w, C_v, C_s, C_4, and is normalized with the total reflectance value [11]. The traditional broadband vegetation indices usually constructed with near-infrared (NIR) and red (R) bands [3], while the VIUPD is computed with the all observed wavelengths. Thus the VIUPD is more suitable for multi-spectral analysis than the EVI and NDVI [11]. The objective of this paper is the description of the development and the validation, using airborne hyper-spectral imagery data, of a non-conventional technique for the vegetation information extraction. This paper validates the UPDM using AVIRIS airborne imagery, and the results provide an expected assumption.

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Author Biography

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