Complex network modeling of spectral remotely sensed imagery: a case study of massive green algae blooms detection based on MODIS data

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Abstract: Feature bands selection and targets classification is of great importance in spectral remotely sensed imagery interpretation. In this work, complex network is adopted for modeling spectral remotely sensed imagery. Subnet is constructed for each band based on spatial neighboring characteristic. Feature bands could be obtained by analyzing and comparing topological characteristics between subnets. After finding feature bands, subnets of feature bands are compounded. Targets classification could be measured by degree distribution of the composited network. This approach is evaluated with empirical experiments based on detecting massive green algae blooms with MODIS data. Feature bands found are coincided with spectral mechanism of green algae. By comparing with FAI, RVI, NDVI, EVI and OSABI methods, our approach improves correct classification rates.

Keywords: complex network; spectral remotely sensed imagery; feature band selection; target detection

1. Introduction

Spectral remotely sensed imagery provides spectral bands with wide range of wavelengths. Energy reflected or emitted from targets over different spectral wavelengths are different. Based on that, targets classification could be distinguished by comparing the spectral response patterns. Due to different spectral response pattern, some bands could be regarded as feature bands for distinguishing targets. Interpretation of spectral remotely sensed imagery is to analyze spectral bands to recognize targets. For example, in comparison with pure water, harmful algae blooms(HABs) have significant absorption bands in around 500nm, 675nm, and reflectance peaks in 550nm and 700nm[1]. Therefore those bands could be regarded as feature bands to distinguish HABs and pure water.

Feature bands selection is first step for interpretation of spectral remotely sensed imagery. Feature bands selection methods are mainly divided into two categories: supervised and unsupervised. The former methods need priori knowledge, which may be unavailable in practice; whereas the latter methods do not need any priori knowledge. Therefore, in this paper we focus on unsupervised methods. There are many successful unsupervised methods for dealing with feature bands selection. The main idea is to find bands which are the most dissimilar with others. For example, bands could not be represented by other bands are selected as feature bands[2]; variance correlation-based sorting are adopted for finding feature bands[3]; spectral distance[4] and mutual information[5] and entropy[6-8] are proposed for filtering feature bands.

Recently, complex network has been employed for image segmentation and classification. Costa *et.al.* proposed a method to transform a image into complex network and showed that the

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combination of the concepts of network hub and 2-expansion of the adjacency matrix be an effective means for image segmentation[9]. Backes *et.al.* studied image modeling by complex network methodology [10-14]. They presented a methodology to shape boundary characterization in which a shaper is modeled into a small world complex network, in which degree, joint degree and fractal dimension of the network are used for describe shape descriptors[10,11]. In [12] they showed that an image network could be generated by trajectories produced by tourist walks. With the generated network mean degree and entropy of two vertices with the same degree are used as texture descriptors. Shortest paths are also used for texture classification[13]. Reducing the number of topological descriptors for texture classification are studied by analyzing energy value of degree histogram of the image-generated network[14]. Sanchez *et.al.*[15] associated a weighted geometrical and fast-computable complex network to images for detecting interest point. Cuadros *et. al.* [16] proposed a method to segment large images by adopting community structure identification. Wu *et.al.*[17]found that dimension between line pixels and non-line pixels were different and a complex network-based method for line detection was proposed. Adopting complex network provides a new way to describe features of image. However, literatures mentioned above mainly focused on grey or RGB image.

Xia *et. al.* [18] first employed horizontal visibility graphs algorithm[19] to transform an hyper spectral remotely sensed imagery into a network and used clustering coefficient measure as descriptor to find feature bands. Horizontal visibility graphs was provided for mapping time series into graphs, in which each data of the series was a node and two nodes were connected if data value of any other node located between them was smaller than them. In [18] sequence of pixels is regards as a time series. Their work was validated on two pieces of hyper spectral remotely sensed imagery: Indian Pines (with 9 types of targets) and Washington DC mall (with 7 types of targets). However, according to horizontal visibility graphs algorithm there are many isolated nodes. The clustering coefficient of isolated nodes is 0. In Section 4, we show that their methods limited in dealing with multi-spectral remotely sensed imagery, especially those with small number of targets.

In our approach, for each band, a band subnet is constructed by abstracting pixels as nodes and two nodes, both of which their difference of reflectance pattern and spatial distance are similar, are linked as an edge. When the imagery is consisted of different kinds of targets, topological structure of the feature-band subnets should be linked sparsely in comparison with non-feature-band subnets. The reason is that for non-feature-band subnets reflectance pattern of all pixels are nearly the same, then neighboring pixels link with each other as a regular network; while for feature-band subnets border between different kinds of targets would be apparently different from a regular network.

The advantage of taking spatial neighborhood characteristic into account is that targets features are transformed into network topological structure which is more robust for sunshine or other environmental influence. In reality, when interpreting spectral remotely sensed imagery one troubling thing is that image features are easily influenced by environmental factors such as atmosphere. When atmosphere environmental changes, spectral response of targets would also change, for example, target captured at different times or different areas has different spectral response patterns. Fortunately, relative response pattern between targets is still remaining. Therefore, we employ geospatial correlation to depict the relative response pattern. In this paper, geospatial correlation is transformed into topological structure of the network generated from the

image. Topological structures are easily obtained and robust for environmental factors.

In Section 2, the approach is detailed. We demonstrate how to transform a spectral remotely sensed image into a subnet according to given band. Band subnet density is defined and we show that this measure could discriminate feature bands. Based on multi-subnet composited complex network model[20,21] feature bands subnets are compounded for recognizing targets. Target characteristics could be described with degree distribution of the composited network. Section 3.1 presents the experimental results of finding feature bands of detecting massive green algae blooms based on the proposed approach by using MODIS data. Detection results are shown in Section 3.2. In Section 4, our approach is validated by comparing with traditional methods FAI, RVI, NDVI, EVI and OSABI. We present the conclusion and discuss future research in Section 5.

2. Complex network modeling of spectral remotely sensed imagery

I indicates an $M \times N$ imagery with $S \geq 1$ bands. $P = \{p_1, p_2, \dots, p_i, \dots, p_{M \times N}\}$ is a set of pixels of I . $d(p_i, p_j)$ is Euclidean distance between pixel p_i and p_j . $B = \{b_1, b_2, \dots, b_s\}$ is set of bands and $f(p_i, b_s)$ indicates value of band b_s at pixel p_i .

Band subnet: Given band b_s , an subnet $G_s(V_s, E_s, b_s)$ of image I could be generated, where $V_s = P$ and $E_s = \{ \langle p_i, p_j \rangle \mid |f(p_i, b_s) - f(p_j, b_s)| \leq k \text{ and } d(p_i, p_j) \leq r \}$. k is similarity threshold value and r is distance threshold value.

Density of band subnet: Given $G_s(V_s, E_s, b_s)$, let $r = \frac{|E_s|}{\frac{1}{2} \times |V_s| \times ((2 \times r + 1)^2 - 1)}$ indicates density

of G_s , where r is distance threshold value.

r measures the subnet connectivity. The numerator of r is number of edges in the subnet and the denominator is the number of edges that could possibly exist in the subnet. When the value of r is closer to 1, it is shown that band value of all pixels are similar. In fact, when r is equal to 1 the band subnet is a regular network.

Supposing that $G_s(V_s, E_s, b_s)$ is an image consisted of targets and non-targets. When the value r of one band subnet is close to 1, that is, there are many edges in this band subnet. It shows that nearly all pixels have similar band value. Then this band could not discriminate targets and non-targets. When the value r is smaller, it means that this band have good discrimination between targets and non-targets. Therefore, for each band $b_s \in B$ construct a band subnet $G_s(V_s, E_s, b_s)$ and calculate the density of band subnet G_s . Sorting all r_s in ascending order and the top rank bands could be taken as feature bands for recognizing targets.

Multiple band composited network: Let $G_{s_1}(V_{s_1}, E_{s_1}, b_{s_1}), G_{s_2}(V_{s_2}, E_{s_2}, b_{s_2}), \dots, G_{s_m}(V_{s_m}, E_{s_m}, b_{s_m})$ are band subnets of image I , $G(V, E, W, B)$ is a network composited by subnets, where $V = P$, $E = E_{s_1} \cup E_{s_2} \cup \dots \cup E_{s_m}$ and $B = \{b_{s_1}, b_{s_2}, \dots, b_{s_m}\}$. $W(\langle p_i, p_j \rangle)$ is a weight value of edge $\langle p_i, p_j \rangle$

which is sum of this edge occurring number in these subnets. When $W(\langle p_i, p_j \rangle) = S$ it means that

all bands values of p_i, p_j are similar, that is, p_i, p_j belong to the same classification.

When degree of one node in the composited network is equal to $(2 \times r + 1)^2$, it means that all feature bands values at this pixel node are similar with all of its neighbors, that is, this node and its neighbors belong to the same classification.

As shown in Fig.1(a), 5×5 image is truncated from real MODIS L1B 500m image¹. There are 7 bands in this image (more details of MODIS data are given in Section 3.1). We just show the first three bands b_1, b_2, b_3 for demonstrating how to construct band subnets. Fig.1(a) shows the image with false color in which both red channel and blue channel are set as band b_1 , green channel is set as band b_2 . We normalize all bands values into [0,1]. Set $r=1$ and $k=0.05$. Bands subnets are shown in Fig.1(b)(c)(d). The 3-bands composited network is shown in Fig.1(e), where weight value of red edge is 3 and weight value of black edge is 2.

Fig.1 Illusion of complex network modeling of spectral remotely sensed imagery

3. Experiments

3.1 Data and preprocessing

In this work, MODIS L1B 500m product data are used for experiments. Reflectance and radiance are provided by this product. There are 7 bands for both of reflectance data and radiance data (wavelength of these bands respectively are 620-670, 841-876, 459-479, 545-565, 1230-1250, 1628-1652 and 2105-2155nm). Information of data is shown in Table 1. These 6 images are preprocessed by doing geometric correction and atmospheric correction in ENVI 5.0. Based on false color composited image (b_1 as red channel, b_2 as green channel and b_1 as blue channel), we choose areas with green algae and no cloud in the study areas.

Table 1 Information of experiments data

ID	Data	Range Area	Number of Pixels	Number of Green Tide Pixels
170	2014-06-19	34° 57892'-35° 06506'N 120° 5731'-121° 4578'E	4070	466
179	2014-06-28	35° 7509'-36° 24645'N 121° 011'-121° 77'E	3808	180
184	2014-07-03	35° 40803'-36° 07537'N 120° 8339'-121° 7767'E	6750	326
195	2014-07-14	35° 97795'-36° 52765'N 121° 3145'-122° 0404'E	4092	107

¹ Download at website <http://rapidfire.sci.gsfc.nasa.gov/cgi-bin/imagery/realtime.cgi>

154	2015-06-03	34° 50012'-35° 18461' N 120° 9735'-121° 8142' E	5621	781
156	2015-06-05	34° 66906'-35° 29091' N 121° 0186'-121.8177' E	5109	529

3.2 Finding feature bands of green algae

In this section, band subnets are constructed for finding feature bands. There are $S=14$ bands of reflectance bands and radiance bands. For each band we construct a subnet. When constructing band subnet, two parameters should be set. One is distance threshold r and another is similarity threshold k . When increasing r there are more neighboring nodes should be compared. In fact, nodes located in close distance may be more similar than those in long distance. Therefore we set distance threshold value $r=1$.

As for similarity threshold k , when difference of band values of two neighborhood nodes is greater than k , the two nodes are regarded as two different kinds of targets. By far, validation of interpretation of remotely sensed imagery usually is done by eye interpretation. Therefore we firstly recognize green algae pixels and sea pixels by eye interpretation. Considering atmosphere influence we use median of difference band value between homogenous pixels. For green algae pixels median of difference band value is calculated as $median_{green} = median(\sum_{i,j} |f(p_i, b_s) - f(p_j, b_s)|)$

where p_i, p_j are green algae pixels. And for sea water pixels median of difference band value is

calculated as $median_{sea} = median(\sum_{i',j'} |f(p_{i'}, b_s) - f(p_{j'}, b_s)|)$ where $p_{i'}, p_{j'}$ are sea water pixels. Then

similarity threshold value of each band is calculated as $k_s = mean(median_{green}, median_{sea})$. With

distance threshold value and similarity threshold value, band subnet $G_s(V_s, E_s, b_s)$ could be constructed according to definition band subnet described in Section 2.

Fig.2 and Fig.3 show the densities of 7 reflectance bands subnets and 7 radiance bands subnets. As show in Fig.2 and Fig.3, value of density of b_2 band subnet is the minimization among all the bands subnets. Wavelength of b_2 band is around 0.841-0.876 μm belonging to near infra-red spectrum. That is to say, energy reflectance pattern between green algae and sea water differs a lot at band b_2 . In fact, this finding corresponds well with the reflectance mechanism of green algae. Literatures [22-24] pointed that green algae had high reflectance in near infra-red wavelength and had nearly no reflectance in red wavelength. Therefore, we choose reflectance band b_2 and radiance band b_2 as feature bands.

Fig.2 Densities of reflectance bands subnets

Fig.3 Densities of radiance bands subnets

3.3 Detecting green algae based on multiple-band composited network

We compound the two feature bands subnets into a composited network. The weight value of edge in the composited network indicates the total number of the edge occurring in the two feature subnets. And we delete those edges whose weight value is not equal to 2. Then remaining edge linking two pixels means that the two pixels have similar value of feature bands.

Degree of nodes is calculated in the composited network. Fig.4-Fig.9 illustrate the degree results. Due to $r=1$, maximization degree of node is 8. When degree of one node is 8, it means that this node and its 8 neighbors have similar value of feature bands. This node and its 8 neighbors belong to the same classification. It is obvious that when the degree of one node is 0 it means that this node could not be the same classification with its neighbors. Due to 500m resolution of MODIS data, green algae scatters sparsely on the sea. Therefore degree of sea water pixel node would be 8 or closer to 8; while degree of green algae pixel node would be small. For nodes locating at border of image their degrees are no more than 5. For nodes which locate at four corners of image their degrees are no more than 3. Those nodes are omitted when we compared the classification result with ground truth. Only pixels whose distance to border is equal or greater than $r=1$ would be considered.

Fig.4 Detection result of 170 image

Fig.5 Detection result of 179 image $g=b_2, b=b_1)$

(a) Degree of nodes **(b) False color composited image ($r=b_1, g=b_2, b=b_1$)**

Fig.6 Detection result of 184 image

(a) Degree of nodes **(b) False color composited image ($r=b_1, g=b_2, b=b_1$)**

Fig.7 Detection result of 195 image

Fig.8 Detection result of 154 image

Fig.9 Detection result of 156 image

Due to both of the feature bands being b_2 we try to study whether reflectance b_2 band or radiance b_2 band could provide enough information for classification. Green algae pixels are regarded as positives and sea water pixels are regarded as negatives. TP indicates number of pixels correctly segmented as true positives. FN indicates number of pixels falsely segmented as negatives. TN indicates number of pixels correctly detected as negatives. FP indicates number of pixels falsely detected as positives. $Precision = TP / (TP + FP)$. $Accuracy = (TP + TN) / (P + N)$. $Recall = TP / (TP + FN)$. Let m indicates degree of nodes which ranges from 1 to 8. Pixel whose degree is less than m is regarded as green algae; pixel whose degree is equal or greater than m is regarded as sea water. We change degree threshold m , measures $Precision$ and $Recall$ change. We

use maximum F-measure ($\frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}$) to evaluate the performance of segmentation. As

shown in Fig.10 when we use reflectance b_2 or radiance b_2 or both of them as feature bands their segmentation performance are almost same. Therefore in view of computational cost we could only use reflectance b_2 or radiance b_2 as feature band.

Fig.10 Evaluation of using only reflectance b_2 or radiance b_2 or both of them as feature bands on 6 images

4. Evaluation and Discuss

In this section, we firstly show that method proposed by Xia *et.al*[18] limits in dealing with spectral remotely sensed imagery with small number of targets classification. And then give the comparison results between our method and five traditional methods.

In Xia's work, horizontal visibility graphs are adopted for transforming an image into a network. In fact, horizontal visibility graphs algorithm is proposed for mapping time series into graph. Therefore pixels from left to right and top to bottom of image are regarded as a time series in their work. Two nodes are connected if any other node locating between them are smaller than them, that is, $x_i, x_j > x_n$ for all n such that $i < n < j$, where x_i, x_j are connected nodes.

For example, there is a 10×10 image truncated from 179, as shown in Fig.11. For simplicity, we just use reflectance band value of b_1 and b_2 to construct networks. The values of the two bands are listed in Table 3(a)(b). Two networks are constructed by adopting horizontal visibility graph. Each node's clustering coefficient is calculated as shown in Fig.12(a)(b). Obviously, there are a lot of isolated nodes which demonstrated as blue color. Difference between topological structure of feature band b_2 and band b_1 is not apparent. Therefore, horizontal visibility graph limits in dealing

with our problem.

Fig.11 10 × 10 image truncated from 179

Table 3(a) Band value of b_1

0.38	0.44	0.46	0.47	0.46	0.43	0.40	0.46	0.54	0.58
0.36	0.42	0.47	0.49	0.48	0.48	0.50	0.52	0.59	0.64
0.33	0.36	0.50	0.56	0.66	0.53	0.50	0.49	0.60	0.64
0.27	0.29	0.50	1.00	0.92	0.57	0.54	0.41	0.47	0.57
0.23	0.22	0.34	0.21	0.27	0.28	0.35	0.45	0.48	0.50
0.20	0.17	0.27	0.27	0.26	0.19	0.07	0.27	0.45	0.50
0.23	0.24	0.36	0.38	0.32	0.22	0.00	0.24	0.40	0.50
0.25	0.30	0.39	0.41	0.34	0.16	0.04	0.19	0.41	0.50
0.25	0.30	0.36	0.38	0.34	0.22	0.14	0.16	0.30	0.44
0.29	0.32	0.39	0.44	0.42	0.35	0.28	0.28	0.35	0.43

Table 3(b) Band value of b_2

0.03	0.03	0.04	0.03	0.03	0.03	0.03	0.03	0.04	0.05
0.02	0.03	0.03	0.05	0.04	0.04	0.04	0.04	0.05	0.05
0.03	0.07	0.18	0.24	0.33	0.09	0.04	0.04	0.05	0.06
0.02	0.10	0.36	1.00	0.86	0.31	0.19	0.07	0.03	0.04
0.01	0.05	0.18	0.12	0.18	0.14	0.17	0.04	0.17	0.05
0.02	0.02	0.04	0.04	0.02	0.10	0.01	0.01	0.03	0.04
0.02	0.02	0.03	0.04	0.08	0.18	0.03	0.01	0.03	0.04
0.02	0.02	0.03	0.03	0.06	0.06	0.03	0.02	0.03	0.05
0.01	0.02	0.03	0.03	0.02	0.01	0.00	0.00	0.02	0.06
0.01	0.02	0.03	0.03	0.03	0.02	0.01	0.01	0.02	0.05

(a) Band b_1

(b) Band value of b_2

Fig.12 Result of nodes' clustering coefficient

In the followings, five traditional methods FAI, EVI, NDVI, RVI and OSABI are adopted for comparing with our method. Rouse *et. al.* proposed *NDVI*(Normalized Difference Vegetation Index)[25].

$$NDVI = (R_{NIR} - R_{RED}) / (R_{NIR} + R_{RED})$$

Where R_{NIR} and R_{RED} are reflectance of near infra-red band and red band. This index pointed that reflectance of vegetation is high at 700nm band. Hu[26] adopted this index to monitor massive green algae blooms chocking around Olympic sailing venue with MODIS 250m resolution data.

Huete *et.al.* proposed *EVI*(Enhanced Vegetation Index)[27]

$$EVI = G \times (R_{NIR} - R_{RED}) / (R_{NIR} + C_1 \times R_{RED} - C_2 \times R_{BLUE} + C_3)$$

where parameters $G = 2.5, C_1 = 6, C_2 = 7.5, C_3 = 1$ for MODIS data. Reflectance of 469nm, 645nm and 859nm are used as R_{BLUE} , R_{RED} and R_{NIR} .

Hu *et.al.* proposed *FAI*(Floating algae index)[24].

$$FAI = R_{NIR} - R_{RED} - (R_{SWIR} - R_{RED}) \frac{(l_{NIR} - l_{RED})}{(l_{SWIR} - l_{RED})}$$

where reflectance of b_2 , b_1 and b_5 of MODIS data are used as R_{NIR} , R_{RED} and R_{SWIR} . l_{NIR} , l_{RED}

and l_{SWIR} are wavelength of near infra-red band, red band and short wave infra-red band.

Shanmugan P et.al proposed OSABI index[23] $OSABI = 10 \times [R_{NIR} - (R_R - R_{NIR})]$ where R_{NIR} and R_R respectively refer to reflectance of near infra-red and red band of MODIS data.

We calculate those five indexes for each pixels of image and normalize them into 0-1. As we change segmentation threshold value (increasing 0.01 every time), we calculate *Precision*, *Recall* and the maximum F-measure. In Section 3.2 and Section 3.3 we set $r=1$ therefore segmentation threshold only refers to 1,2,3,4,5,6,7,8. In this section for comparing with the above index methods mentioned we should increase r to enlarge degree value. Obviously when r is increasing, it means that more neighboring nodes should be considered. On the other hand, larger r would obstruct the geospatial correlation. Through intensive experiments we adjust the parameter r and finally choose $r=5$ (the maximum degree could reach to 120). We also normalize degrees into 0 to 1. Fig.13 gives the comparison result between our method and five traditional methods. It is shown that our method perform better in 170, 179, 184 and 195 images but in 154 and 156 image F value of our method is 0.03 lower than OSABI methods. Fig.14 gives recall comparison results between our method with the five methods, which shows that our method perform better than them.

Fig.13 Comparison result between our method and five traditional methods

Fig.14 Recall Comparison

5. Conclusion and Future Work

In this work, a novel approach is proposed to choose feature bands and detect targets by transforming a remotely sensed imagery into a multiple-band composited network based on spatial neighboring characteristic. For each band, a band subnet is constructed by abstracting pixels as nodes and pixels similarly as edges. It is shown that topological characteristic of feature bands subnets differs a lot with other bands. Based on that, feature bands subnets are compounded for detecting targets. Target characteristics could be described with degrees of the composited network. This approach is validated by detecting massive green algae blooms with MODIS data. Feature bands are found through topological analysis of band subnets, which are coincided with spectral mechanism of green algae. By comparing with FAI, RVI, NDVI, EVI and OSABI methods, our method can improve correct classification rates.

Resolution of MODIS data is 500m. Due to this low resolution, green algae blooms scatter on the sea thus the area of green algae blooms pixels is small while the area of sea water pixels is large. Based on that nodes with small degree could be regarded as green algae pixels and nodes with large degree could be regarded as sea water pixels. When using high resolution of imagery, such as LADSAT (resolution 30m), node with small degree would be border between green algae and sea water. In the future, high resolution spectral remotely sensed imagery would be used for validating our approach.

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