Ms. Neha Bhatt, Mr. IndrJeet Rajput, Mr. Vinitkumar Gupta / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 www.ijera.com
Vol. 3, Issue 3, May-Jun 2013, pp.174-179

Classification of Multi-date, Tempo-Spectral data using NDVI values

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Abstract— NASA launched the Earth Observing System's flagship satellite "Terra," named for Earth, on December 18, 1999. Terra has been collecting data about Earth's changing climate Normalized Difference Vegetation Index (NDVI) is a simple graphical indicator that can be used to analyze remote sensing measurements. These indexes can be used to prediction of classes of Remote Sensing (RS) images. In this paper, we will classify the Terra image on NDVI values of 5 different date's images (Captured by Terra satellite). For classifying images, we will use formulae, which is based on similarity measure. It will compare the clustered image with the Reference image based on the equation, it will classify the image. It is simple process, which can classify much faster.

Keywords*-Terra, Normalized Difference Vegetation Index (NDVI), Remote Sensing, Multi date.*

I. INTRODUCTION

The evaluation of the tempo -spectral data is very useful in environment field [1]. In this paper, we propose the technique for finding similarity based on reference images. The Vegetation Index (VI) based on the image taken through Remote Sensing can be used to identify the objects [1]. Normalized Difference Vegetation Index (NDVI) is one of the popular Vegetation Index. In this paper, we are using Terradata to compute the similarity.

Terra carries five state-of-the-art sensors that have been studying the interactions among the Earth's atmosphere, lands, oceans, and radiant energy. Each sensor has unique design features that will enable scientists to meet a wide range of science objectives. The five Terra onboard sensors are:

- ASTER, or Advanced Spaceborne Thermal Emission and Reflection Radiometer
- CERES, or Clouds and Earth's Radiant Energy System
- MISR, or Multi-angle Imaging Spectroradiometer
- MODIS, or Moderate-resolution Imaging Spectroradiometer
- MOPITT, or Measurements of Pollution in the Troposphere

Because Terra's five sensors share a platform, they collect complimentary observations of Earth's surface and atmosphere. These varying perspectives of the same event can yield unique insights into the processes that connect Earth's systems.

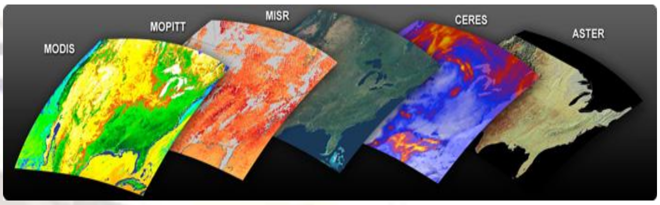


Figure1: Terra Sensor

NDVI value of an image can be calculated based upon the following formulae.

$$NDVI = \frac{IR - RED}{IR + RED}$$

Where IR (Infra-Red) denotes the value in the Infra-Red band and RED denotes the value in Red band. As image consist of many bands, NDVI uses these 2 bands for its calculation.

Template matching is one of the simple techniques used from past many decades. It is a basic technique for image as it can answer too many questions related to image [2]. We give the faster algorithm Sum of Squared Difference on NDVI values of Remote Sensing data. Also the intention of this paper is not to say that this measure opposes the other measures.

II. RELATED WORK

Integration of different and complementary sensor images such as optical and radar remotely-sensed images has been widely used for cloud cover removal [1] and achieving better scene interpretation accuracy [2, 3]. The integration may be done by image mosaicking or data fusion which are accomplished either at the preprocessing stage [4] or the postprocessing stage [2]. Sensor-specific classifiers are commonly used. For example, classifiers based on image tonal or spectral features are used to classify optical images [2]. In other cases, classifiers based on texture features are used for recognizing cloud types [5] and improving the urban area classification result for optical images. For radar image interpretation, classifiers based on various texture models were used [6, 7, 8], but problems may arise if *homogeneous-region* land cover objects exist in the radar image [9].

We have observed that both optical and radar images consist of homogeneous and textured regions. Aregion is considered as homogeneous if the local variance of gray level distribution is relatively low, and a region is considered as textured if the local variance is high. Our further investigations found that land-cover objects can also be grouped into homogeneous and textured land cover objects which offer better discrimination in each group. Based on these findings we have proposed an integrated multi-sensor classification scheme [1]. The same procedure can be used for classifying optical or radar input images. We use the multivariate Gaussian distribution to model the homogeneous part of an image, and use the multinomial distribution to model the gray level co-occurrences of the textured part [9]. We apply a spectral-based classifier to the homogeneous part anda texture-based classifier to the textured part of an image. These classifiers use maximum-likelihood decision rule which work concurrently on an input image.

Low-level data fusion may be done to improve radar image classification accuracy or to exploit the synergy of multi-sensor information. The data fusion method may include algebraic operations, the principal component transformation or the Karhunen-Loeve transform, FCC or IHS tranformation, augmented vector classification, and hierarchical data fusion. We have utilized the intensity transformation based on the Karhunen-Loeve transform [11] and hierarchical data fusion [4]

The classification scheme was discussed in [1]. Basically, there are three parameters that control the proposed classifier:

(a) A threshold value that decides if a pixel belongs to either the homogeneous or the textured region,

(b) Type of each land cover object (homogeneous, textured, or both), and

(c) The window size over which the texture meaures are computed.

The threshold value can be tuned so that we can even have a fully spectralbased classifier or a fully texture-based classifier if it is necessary. The type of each land cover object can be determined based on the labeled training samples. We can use a window size as small as 3x3 if there are roads or other line-shaped objects, or a window size of 9x9 if larger objects are contained in the image.

Several studies have found that the temporal variations of MODIS vegetation index (NDVI/EVI) values are related to climatic conditions such as temperature and precipitation [12-15]. The authors discovered that the interannual variation in Normalized Difference Vegetation Index (NDVI) and Enhanced vegetation index (EVI) values for specific eight-day periods was correlated with the phenological indicators [12].It has been demonstrated that vegetation covers of different moisture conditions or different species compositions have different variation patterns in the time series of the MODIS Enhanced Vegetation Index (EVI) values[16]. Template matching isa fundamental method of detecting the presence or theabsence of objects and identifying them in an image. Atemplate isitself an image that contains a feature or an object or a part ofa bigger image, and isused to search a given image for the presence or the absence of the contents ofthe template. This search iscarried out by translating the template systematically pixel - by-pixel all over the image, and at each position ofthe template the closeness of the template to the area covered by it ismeasured. The locationat which the maximum degree of closeness isachieved isdeclared to be the location of the object detected [17].Template matching is one of the simple techniques used from past many decades. It is a basic technique for image as it can answer too many questions related to image [27]. We give the faster algorithm Sum of Squared Difference on NDVI values of Remote Sensing data. Also the intention of this paper is not to say that this measure opposes the other measures.

While vegetation is the concern, there should be accuracy in classifying the image based on proper criteria which must leads to a valid conclusion. Existing models of the vegetation dynamic are typically ignores the spatial correlations [19]. There are many numbers of techniques which are used for the template matching. It includes template matching strategy using template trees growth [20], Comparison based template matching [21], Digital Image processing [22], Correlation techniques in Image processing [23]. Multi-date sequence of the data can be used to quantifying the time-space structure of vegetation [24]. As an example, remotely sensed image series of NDVI [25] and Enhanced VI (EVI) gathered from the different sensors can be directly used in analysis of the structural and functional characteristics of land covers [26]. For the short lead-time applications in agricultural water management and forest-fire assessment, a spatiotemporal model that captures spatial variation patterns in vegetation conditions and phenology is required. In this paper, we propose a predictive multidimensional model of vegetation anomalies that overcomes the limitations of existing approaches. The model is based on a two-step process. The first step describes the deterministic component of vegetation dynamics through an additive model, including seasonal components, interannual trends, and jumps. The spatial dependences are neglected in the first step. The deterministic model (DM) represents a filtering procedure able to generate a new stationary time series of anomalies (residuals). The second step assumes that the residual component of the DM is a stochastic process which exhibits systematic autoregressive (AR) and spatial dependences. Then, the dynamics of the anomalies are analyzed through a multidimensional model (space-time AR (STAR) model), which accounts for the AR characteristics and the spatial correlations of the remotely sensed image sequences [18].

III. APPROACH

There are many approaches to classify the image sensed using Remote Sensing Satellites.

A. *Classical Approach*

There are many techniques available for classifying an image. Some of them are listed below.

- Comparison based template matching
- Digital Image Processing
- Correlation techniques
- Pattern matching
- Time-space structure of vegetation

B. *Our Approach*

NDVI values can be calculated using the following algorithm.

For each i in range
ndvi_lower_part = (nir_value[i] + red_value[i])
ndvi_upper_part = (nir_value[i] - red_value[i])
ndvi = ndvi_upper_part/ndvi_lower_part

Algorithm1: Calculate NDVI values

Similarity Measure	Formula
Sum of Squared Difference (SSD)	$\sum_{(i,j)\in W}(I_1(i,j)-I_2(x+i,y+j))^2$
Sum of Absolute Difference (SAD)	$\sum_{(i,j)\in W}\lvert I_1(i,j)-I_2(x+i,y+j)\rvert$
Zero-mean Sum of Absolute Difference (ZSAD)	$\sum_{(i,j)\in W}\lvert I_1(i,j)-\bar{I}_1(i,j)-I_2(x+i,y+j)+\bar{I}_2(x+i,y+j)\rvert$
Locally scaled Sum of Absolute Difference (LSAD)	$\sum_{(i,j)\in W}\lvert I_1(i,j)-\frac{\bar{I}_1(i,j)}{\bar{I}_2(x+i,y+j)}I_2(x+i,y+j)\rvert$

Table1: Similarity Measures

Table 1shows some of the similarity measures available which can be applicable to image data. This type of similarity measure we called it as correlation based similarity measure. In this technique, we are taking window of a small size and the pixels in that region are compared with the reference of that type of image and small window of that region. This method checks the similarity pixel by pixel.

There are many other similarity measures like Sum of the Squared Difference (SSD), Zero-mean Sum of the Squared Difference (ZSSD), Locally Scaled Sum of the Squared Difference (LSSD), Normalized Cross Correlation (NCC), Zero mean Normalized Cross Correlation (ZNCC) and Sum of Hamming Distance (SHD).

Consider the equation shown below:

$$\sum \frac{Abs(I1(i,j)-I2(x+i,y+j))}{I1(i,j)+I2(x+i,y+j)}$$

Equation [1]

Above formulae is a proposed formula to measure similarity. It is based on Sum of Absolute Difference and it can provide nearer result to the Sum of Absolute Difference. Now apply above formulae to Unknown image with Reference image. Images used for applying above algorithm is as shown below.

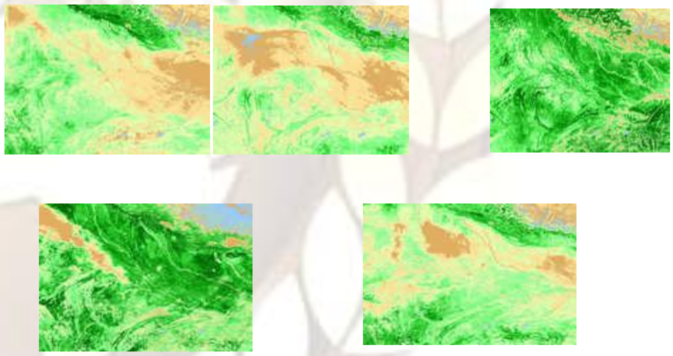


Figure 2: 18 Feb 2013, 15 Jan 2013, 10 Dec 2012, 8 Nov 2012, 2 Oct 2012 Respectively

Below is the file used for Reference classes

2/10/12	8/11/12	10/12/12	15/01/13	18/02/13	Ref-Class
137.89	103.56	102.22	132.44	165.11	1
157.56	106	92.33	127.33	168	2
115.56	93.67	113.89	147.22	155.44	3
133.56	97	105.67	129.44	156.44	4
142.33	96.67	104.78	117.11	162.22	5
96.22	116.44	153.89	158	131.89	6
103.56	108.44	141	156.78	141.11	7
102.56	111.33	161	156.11	129.78	8
100.44	123.11	156.44	154.33	105.78	9
97.56	113.89	167	157	131	10
116.11	111.89	156.89	126.67	136.78	11
71.44	66.22	53	60.33	82.67	12
78.78	76.44	72.67	81.11	72.33	13
79.22	71.67	61	60.89	83.11	14
74.11	75	74.33	77	83.44	15
115.78	102.44	107	115.44	101.33	16
106.33	101.11	100.22	99.56	96.67	17
142.89	120.44	114.56	124.44	104.11	18
160.78	127.44	140	125.89	110.89	19
156.22	119.89	136.78	126.56	107.11	20

Table2: Reference File

Below is the file used to compare unknown class.

2/10/12	8/11/12	10/12/12	15/01/13	18/02/13	Cluster No
101.58	4.7	119.21	0	111.11	1
1.01	90.72	0	114.33	0	2
70.25	73.96	66.27	78.99	91.33	3
101.08	97.52	99.38	99.32	96.68	4
98.02	98.76	107.31	114.17	114	5

Table3: Cluster File

Proposed Work:

1. Take 5 different dates Reference and Unknown cluster images.
2. Calculate NDVI images for all 5 images using algorithm 1 as shown above.
3. Get the Unknown interested regions from the image and collect the NDVI values into 1 file.
4. Normalize NDVI values of -1 to 1 into 0 to 200 by
   using formulae:
   ndvi_new = ndvi_old x 100 + 100
5. Make the Reference file and Unknown cluster file as shown above in Table 2 and Table 3.
6. Apply Equation [1] given above for these 2 files and get the class label.
7. Get the output as shown in Table4. It will contain the class in which unknown class is classified.

IV. IMPLEMENTATION

To calculate NDVI values, we can use GDAL library. GDAL is one type of Translator library, generally used for raster Geospatial data format and which is open source. We will use Python language for programming and we can use Eclipse IDE. We can implement the functionality shown in Algorithm1 in Python after embedding GDAL library into it. After calculating NDVI values, we can use this NDVI data to apply Equation [1]. Here, we will use .Net technology with C# as programming language to implement Equation1. Fig. 4 shows the design of the implementation of algorithm. It will take input as Reference File and Cluster File and it will produce Output file which will contain classification details.

159.74	130.6	147.48	136.85	120.94	19
1.01	90.72	0	114.33	0	1
70.25	73.96	66.27	78.99	91.33	15
101.08	97.52	99.38	99.32	96.68	17
98.02	98.76	107.31	114.17	114	16

Table4: Output File

After classification process when we can compare the resulted Reference and unknown cluster it can be shown as a graph.

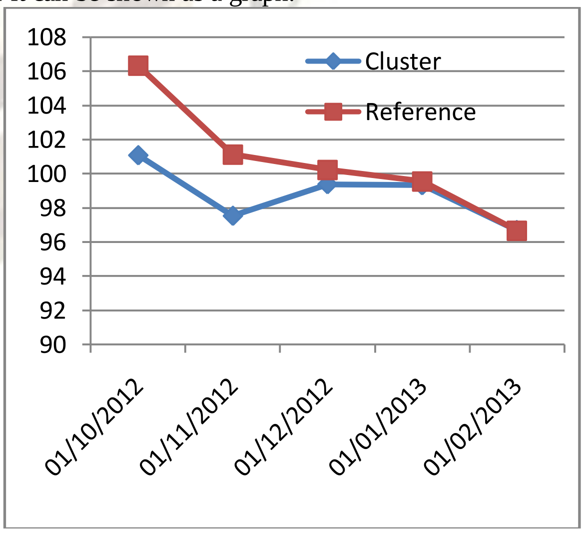


Figure 3: Analysis

V. CONCLUSION

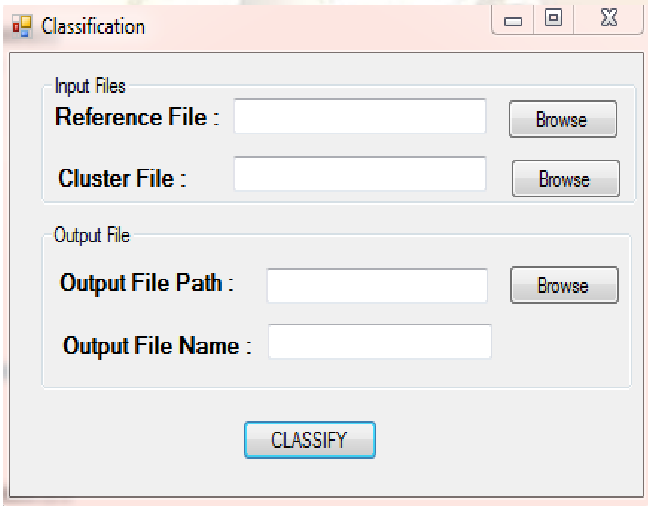
From above implementation results, we can conclude that this algorithm is much faster compared to other approaches as it includes small mathematical calculation and it take O (n) time to compute the result. The 'n' value depends upon number of clusters that needs to classify.

VI. FUTURE WORK

This algorithm can also used to enhance the perfection by including Standard deviation. Also it can't be used for needs where some dates are having more importance and need to give more preference to that particular date. In that case, we need to modify this algorithm to some point. This feature can also be implemented using Sum of Absolute Difference. In that case, we can get similar value to that of Sum of Squared Difference.

ACKNOWLEDGMENT

We would like to thank the School of Computer Science and Engineering, GTU, for giving us such an opportunity to carry out this research work and also for providing us the requisite resources and infrastructure for carrying out the research.



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