Classification of Multi-date Image using NDVI values

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Abstract— Advance Wide Field Sensor (AWiFS) of IRS P6 is an improved version of WiFS of IRS-1C/1D. AWiFS operates in four spectral bands identical to LISS III (Low-Imaging Sensing Satellite). 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 AWiFS image on NDVI values of 5 different date's images (Captured by AWiFS satellite). For classifying images, we will use an algorithm called Sum of Squared Difference (SSD). It will compare the clustered image with the Reference image based on SSD and the best match on the basis of SSD algorithm, it will classify the image. It is simple 1 step process, which will be faster compared to the classical approach.

Keywords- AWiFS, Normalized Difference Vegetation Index (NDVI), Sum of Squared Difference, 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 Advanced Wide Field Sensor's (AWiFS) data to compute the similarity. ERDAS Imagine is one of the world's geospatial data analyzing system. It can be used for image processing and pattern recognization of the Remote Sensing data. We can generate NDVI values of the image using ERDAS Imagine software which can be further be used to classify the image based on Sum of Squared Difference.

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. A region 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 offers 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 and a 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 spectral based 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 is a fundamental method of detecting the presence or the absence of objects and identifying them in an image.

A template is itself an image that contains a feature or an object or a part of a bigger image, and is used to search a given image for the presence or the absence of the contents of the template. This search is carried out by translating the template systematically pixel - by-pixel all over the image, and at each position of the template the closeness of the template to the area covered by it is measured. The location at which the maximum degree of closeness is achieved is declared 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*

The classical approach which we are going to discuss is a two step process. The first step denotes the deterministic component of vegetation dynamics through an additive model, interannual trends, jumps, and including seasonal components. In the first step, spatial dependences are neglected. The deterministic model (DM) shows a filtering procedure which able to generate a new stationary time series of residuals (anomalies). In the second step, we are assuming that the residual component of the DM is a stochastic process which exhibits spatial dependences and systematic autoregressive (AR). After that, the dynamics of the anomalies are analyzed through a space-time AR (STAR) model (multidimensional model), which accounts for the spatial correlations and the AR characteristics of the remotely sensed image sequences.

B. SSD (Sum of Squared Difference) Algorithm – Our Approach

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)	$\sum_{(i,j)\in W}\lvert I_1(i,j)-\frac{\bar{I}_1(i,j)}{\bar{I}_2(x+i,y+j)}I_2(x+i,y+j)\rvert$

Table.1 Similarity Measures

Table 1 shows 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. Sum of Squared Difference is one of the simplest methods used for similarity measure. In this technique, we are taking difference of pixel of original image which all the reference image and then squaring the value, image which is having less value for Sum of Squared Difference is consider as the best matching for the original image.

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).

To use our method on NDVI values, we need to have a reference class based on which, we have to classify the clustered image. The clustered image's NDVI value is compared with the reference NDVI values and Sum of the Squared Difference is calculated based upon that, the reference class having less value of Sum of Squared Difference.

IV. IMPLEMENTATION

Sum of Squared Difference can be implemented using the formulae 1 as shown in Table1. Here, we will use .Net technology with C# as programming language to implement SSD Algorithm. The design of the implementation of algorithm will take input as Reference File and Cluster File and it will produce Output file which will contain classification details. After classification process when we can compare the resulted Reference and unknown cluster.

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 is still not perfect and requires huge number of improvements. 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.

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