

Satellite Image Segmentation and Classification of Environmental Analysis

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Abstract:

Conventional supervised classification of satellite images makes use of one multi-band photo and coincident ground observations to assemble spectral signatures of land cover classes. It will take a satellite image and give it as input. Training will be done before itself like how a crop, tree, water body, Empty land, Buildings parameters will be done. Then this input image is given initially speckle noise will be high in the image that will be removed first. The classification will be done with the help of SVM algorithm.

Keywords —Support Vector Machine, Speckle Noise, Signal to Noise Ratio, Accuracy.

I. INTRODUCTION

In remote sensing images, a lot of predictions are often made with none intervention of the person. Remotely sensed image is digital representations of the world, by using this, places which can't be accessed is viewed by the remote sensing images, this may encourage the method of these interior parts. In a remotely sensed image data, each pixel represents a neighborhood of the world at a selected location. If a pixel satisfies a particular set of criteria then that pixel is assigned to the category that corresponds to those criteria. This process is referred as image classification. Presently, image classification method is often grouped into two main categories count on the image primitive i.e. pixel based and object-based method. Pixel based methods classify individual pixels without taking the under consideration any neighborhood or spatial information of the pixel. Object/ Region

based methods also are ready to handle high resolution imagery which aggravates the classification process for many pixel-based methods. These results were compared with the MOKNN and MOSVM. Modified algorithms which gives the better result comparing with the existing algorithms.

RELATED WORKS

Adhoc CLEAN algorithms [1] have been developed to improve the spatial resolution of bistatic images and MSAR images (Multistatic Synthetic Aperture Radar) which produces images with 1m spatial resolution, however it is applicable for processing coarse range resolution. Zhao et al.,[2] integrated spatial, spectral and spatial location cues by using CRF model (Conditional Random Field) to produce high

resolution remote sensing image. The proposed method solves spatial variability problem, yet it fails to use rich information available in spatial location cues. The integration of spatial, spectral and temporal resolution [3] using hidden markov model, PSM/MS model and filtering methods are wont to obtain high spatial-temporal – spectral resolution fused data. the most advantage is low noise distortion within the obtained fused image but its efficiency is low.

Correcting the geometric errors in Night time Lights Time series image (NLT) have been done by Zhao et al., [4] using GDP growth rates, cross correlation between reference image and candidate image enables to find error DN value. The population corrected NLT is used to produce accurate results but it generates uncertain errors on corrected DN values in night time light images. Landsat MSS L1G (Multispectral Scanners Landsat 1 Generation) images [5] are used to analyse multi-temporal changes and should be free from geometric distortions. DEM (Digital Elevation Model) and MSS sensor parameters are used for ortho-rectification and geo-referencing to improve the accuracy of geometric corrections, proposed method is evaluated quantitatively and has high accuracy.

Lewis et al., [6] proposed cloud-shadow atmospheric correction method, which corrects the pixels with similar optical properties like cloud pixels, shadow pixels and sunlit pixels. This approach solves adjacency error between bright and dark objects but the success rate is low because it depends on the choice of appropriate cloud.

SAR (Synthetic Aperture Radar) [7] image has less capability in measuring ground deformation information due to Atmospheric Phase Delay Effects (APDE). This method is more suitable in studying volcanic deformation and infrequently shows unexpected errors on temporal data.

Kowkabi et al.,[8] to accurately retrieve the top member class by enhancing the spectral information of satellite imagery. Clustering and over segmentation-based pre-processing (COPP) has been developed by incorporating spectral and spatial information that identifies spatially homogenous zones with the good spectral purity

score. The proposed algorithm doesn't presume the presence of pure pixels. Spectral unmixing is a crucial research topic within the field of remote sensing, that aims to unmix the spectral signature of different classes by enhancing the spectral features within the observed scene.

Drumetz et al.,[9] developed Extended Linear Mixture Model (ELMM), that permits a pixel wise spatially coherent local variation of the top members, resulting in scaled versions of reference endmembers. The scaling parameter estimates the quantity of spectral variability in synthetic data and may be corrected using physical model. It gives good enhancement results for endmember class than Constrained. Least Squares Unmixing (CLSU) algorithm. it's less accurate result for aerial images like Lidar. Kraft et al., [10] studied differences between Google earth imagery and satellite imagery to classify different classes on the world surface.

II. LIMITATIONS OF EXISTING SYSTEM

- Most of the prevailing methods were developed for the fusion of “low” spatial resolution images like SPOT and Land-sat TM they'll or might not be suitable for the fusion of VHR image for specific tasks. Additionally, operator dependency was also a main problem of existing fusion techniques, i.e. different operators with different knowledge and knowledge usually produced different fusion results for same method.
- The jury remains out on the advantages of a fused image compared to its original images. there's also a scarcity of measures for assessing the target quality of the spatial and spectral resolution for the fusion methods

III. PROPOSED SYSTEM

This project uses the methodology of k-means clustering for segmentation and support vector machine for classification.

This project is a proposal for calculate the percentage of the given environment. The calculation gives the knowledge about the concept of globalization and over population.

IV. SYSTEM DESIGN

The proposed architectural model of this project is as shown in the figure 1.

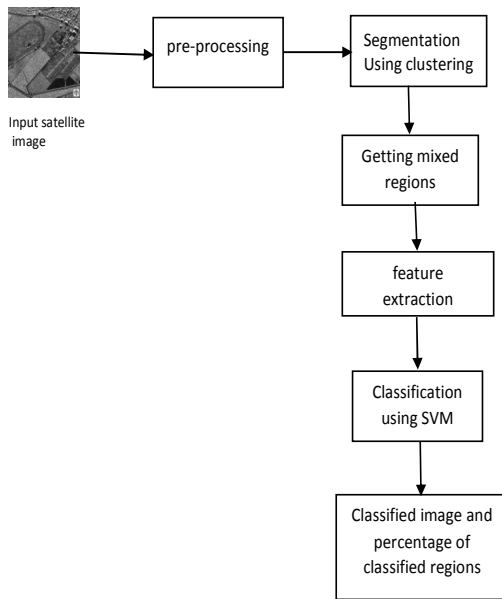


Fig.: 1 Overall Architecture

The proposed model of this project is as shown in the figure 1 which consists of four main phases as follows,

1. pre-processing
2. segmentation
3. feature extraction
4. classification

Pre-processing

Pre-processing functions involves the operations required prior to the most data analysis and consists of processes aimed at geometric correction, radiometric correction and atmospheric corrections to enhance the power to interpret the image components qualitatively and quantitatively. These process correct the info for sensor irregularities and removing (radiometric corrections) unwanted sensor distortion or atmospheric noise.

Segmentation

Segmentation In pre-processing, image segmentation separates objects of interest from back ground through various methods in image processing i.e. removal of unwanted particles from the image by their intensity values. It complements the picture pleasant to get exact result. A binary picture is produced through the Watershed transform 1(black) is assign for watershed and 0(white) is assigned to land areas. It represents the brightness of every point within the picture. After segmentation getting the mixed regions.

Feature extraction

Feature extraction involves reducing amount of resources required to explain large set of knowledge. During this process if the input file of an algorithm is just too large to be performed then it often transformed into a reduced set of features. Features are extracted either at the given input image. during this work textural features are considered for further processing. Grey level histogram is employed during this work to extract the features like skewness and kurtosis. Skewness may be a measure of the symmetry during a distribution. A symmetrical dataset will have a skewness adequate to 0. So, a traditional distribution will have a skewness of 0. Skewness essentially measures the relative size of the 2 tails. Kurtosis may be a measure of the combined sizes of the 2 tails. It measures the quantity of probability within the tails. the worth is usually compared to the kurtosis of the traditional distribution, which is adequate to 3. If the kurtosis is bigger than 3, then the dataset has heavier tails than a traditional distribution. If the

kurtosis is a smaller amount than 3, then the dataset has lighter tails than a traditional distribution.

Classification

In order to classify a hard and fast of records into one-of-a-kind training or categories, the connection between the information and the classes into which they are classified should be well understood. It is the process of assigning pixels inside the image to categorize them. Support vector machine with Artificial Neural Network set of rules is applied to categorize the results. Multi Support vector machine is a supervised learning with associated learning algorithms that analyse information used for classification. This maximizes the margin between two classes. Nonlinear classifiers are implemented by applying kernel trick to maximum-margin hyper plane. The resultant algorithm is analogous with the exception that every scalar product is substituted by a nonlinear kernel function. this allows the algorithm to regulate the maximum-margin hyper plane in an altered feature space. After classification, it will produce the classified image with percentage of that region.

ALGORITHM OR METHODOLOGY:

K-MEANSCLUSTERING FOR CLASSIFICATION:

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SVM (SUPPORT VECTOR MACHINE) FOR CLASSIFICATION:

Support Vector Machine Support Vector Machine is a new approach to supervised pattern class which has been successfully implemented to a wide variety of sample recognition issues and it's also a education algorithm for getting to know classification and regression policies from facts. SVM is most suitable for running as it should be and correctly with high dimensionality function spaces in addition to that SVM is based totally on strong mathematical foundations and effects in simple manner and very effective algorithms. The general SVM algorithm builds a binary classifier.

This system is offered with a set of schooling examples, (x_i, y_i) where the x_i are the facts instances and the y_i are the labels indicating which magnificence the instance belongs to. For the sample recognition trouble, $y_i = +1$ or $y_i = -1$. A training example (x_i, y_i) is called superb if $y_i = +1$ and bad otherwise. SVM assemble a hyper aircraft that separates training and tries to achieve most separation among the classes. Separating the classes with a huge margin minimizes a bound on the predicted generalization error. The most effective version of SVM known as Maximal Margin classifier, constructs a linear separator = zero between two finest hyper plane) given by $W^T x_i - b$ classes of the examples. The free parameters weights W vectors that's orthogonal to the hyper aircraft. These parameters are acquired via threshold value solving the subsequent optimization trouble using in which D_i corresponds to class labels, which assumes value $+1$ and -1 . The times with not null weights are referred to as aid vectors. In the presence of outliers and wrongly classified training examples it may be beneficial to permit some training mistakes so as to avoid over fitting.

$$\text{Minimize } \frac{1}{2}W^2$$

Subject to $D_{ii}(WT-\gamma) \geq 1, i=1, \dots, l.$

Where D_{ii} corresponds to class labels. In the presence of outliers and wrongly classified training examples it may be beneficial to permit some training mistakes so as to avoid over fitting. A vector of slack variables ξ that measure the quantity of violation of the constraints is brought and the optimization hassle referred to as soft margin is given under the minimization of the objective feature causes most separation between two instructions with minimum wide variety of points crossing their respective bounding planes.

$$\text{Minimize } C \sum_{i=1}^l \xi_i + \frac{1}{2}W^2$$

$$W = \gamma$$

Subject to $D_{ii}(W^T \cdot Y)_{\geq 1, i=1, \dots, l.}$

$$\xi_i \geq 0$$

The gain of the dual formula is that it permits an efficient studying of non-linear SVM separators, by means of introducing kernel functions. Technically, a kernel characteristic calculates a dot product among two vectors that have been (nonlinearly) mapped into a excessive dimensional feature space. Since there is no want to carry out this mapping explicitly,

$$f(x) = \text{sgn}[w^T \cdot X \cdot Y]$$

Feasible even though the dimension of the real function space may be very excessive or maybe infinite. The parameters are acquired by way of solving the subsequent non linear SVM dual formula (in Matrix form)

Table1: confusion SVM matrix

Class	crop	water	crop_ other	trees	plants
crop	105	20	15	20	68
water	45	11	13	12	40
crop_ other	22	5	25	7	33
trees	105	25	15	117	2
plants	30	8	20	8	34

Classification feed ahead Artificial Neural Network

The information used for training and testing include feature vectors with 9 functions each. The classification lessons are cancerous mobile and non-cancerous mobile. The functions had been chosen so that the styles of normal cells do now not must be distinguished. The great classification end result has been received by the use of Feed ahead Artificial Neural Network. Mat lab Neural Network Toolbox has been used to teach and to check the network. The great network had 10 hidden layer neurons. The cross-validation has been used for more reliable education and testing. Neural networks include a large class of different architectures. In many cases, the problem is approximating a static nonlinear, mapping $f(x)$ with a neural community $f_{NN}(x)$, where $X \in RK$. The beneficial neural networks in characteristic approximation are Multilayer Layer Perceptron (MLP) and Radial Basis Function (RBF) networks. Here we focus on MLP networks. The MLP consists of an input layer, numerous hidden layers, and an output layer.

V. RESULTS AND DISCUSSION

In this project fig:2 is the input given to the trained machine. After input is given the machine automatically done the preprocessing, segmentation and classification. The output of classified image and classified percentage is shown in fig:4&fig:5



Fig.2input image.

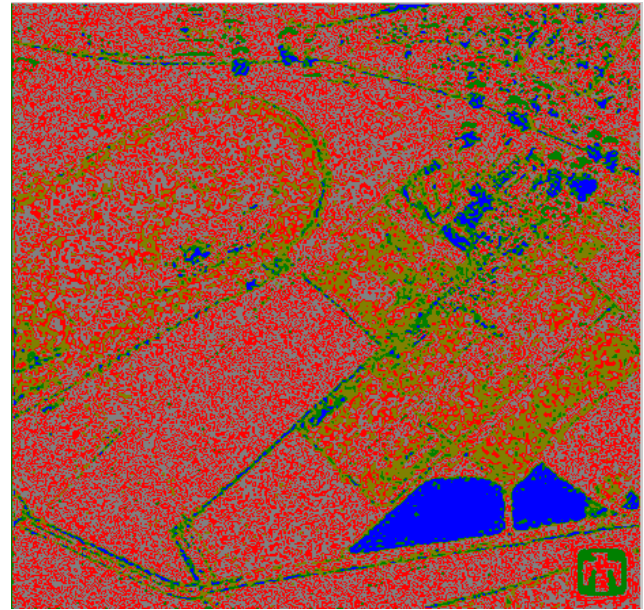


Fig. 4 classified output image



crop plants tree

Fig. 3some of trained images

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1  %%
2
3  clear all;
4  close all;
5  clc;
6
7  [baseName, folder] = uigetfile('*.csv','*.*'); 'Select Training Data Set';
8  fullFileName = fullfile(folder, baseName);
9  file_ind = fopen(fullFileName); %training areas total no of classes are 5
10
11  C = textscan(file_ind, '%f%f%f', 'delimiter', ','); % Import data
12  fclose(file_ind);
13  physchars = [C(1) C(2) C(3)]; % inputs to neural network
14
15  [baseName, folder] = uigetfile('*.png;*.jpeg;*.jpg;*.tif;*.tiff','Select Image File');
16  fullFileName = fullfile(folder, baseName);
Command Window
New to MATLAB? Watch this Video, see Examples, or read Getting Started.
460
461
Percentage of Gray(Lable1, Crops): 38.086515Percentage of Blue(Lable2, Water): 4.520645Percentage of Red(Lable3, Crop_othe
```

Fig. 5classified output image percentage

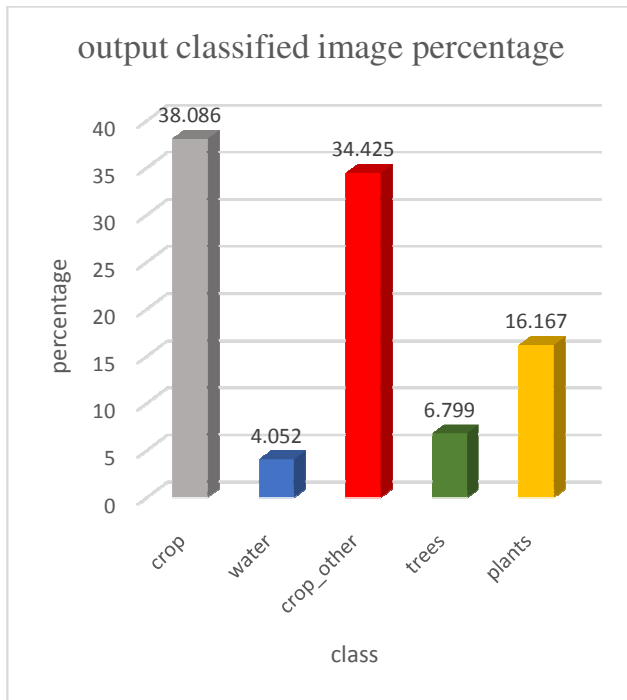


Fig.6 analysis of classified image

VI. CONCLUSION

This project gives a summary on automated satellite image classification methods and compares several reviews done by various researchers. within the literature, researchers have presented survey on satellite image classification methods and evaluated the performance against different datasets. This project summarizes the varied reviews on satellite image classification methods and techniques. The summary helps researchers to pick appropriate satellite image classification.

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