Feature Extraction of a Multispectral Image by a Neural Approach

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Abstract

Ensemble of artificial neural networks often has better performance than any of the single learned ANN in the ensemble. And the combination of remote sensing and geographic ancillary data is believed to offer improved accuracy in land cover classification. This paper focuses on the Image Analysis of Remote Sensing Data Integrating Spectral and Spatial Features of Objects in the area of satellite image processing. We have used the multi-spectral remote sensing data is used to find the spectral signature of different objects. Here, we used a neural approach for finding the FCC image form multispectral image to show land, Vegetation and water.

Keywords

Remote Sensing, Spectral Wavelength, Solar Zenith Angle, Multi-Spectral Images

I. Introduction

In the present scenario of the world, the information technology plays a major role in the world economics; if we get the timely information about the resources of the city then we could plan and manage the resources of the city in a better way, for the economically and environmentally sustainable urban development Land cover and the human or natural alteration of land cover play a major role in global scale patterns of climate. Rapid urbanization and urban sprawl have significant impact on conditions of urban ecosystems. Changes in land use and land cover are directly linked to many facets of human health and welfare, including biodiversity, food production, and the origin and spread of disease.

II. Remote Sensing

Remote sensing is a technology used for obtaining information about a target through the analysis of data acquired from the target at a distance. It is composed of three parts, the targets - objects or phenomena in an area; the data acquisition - through certain instruments; and the data analysis again by some devices. This definition is so broad that the vision system of human eyes, sonar sounding of the sea floor, ultrasound and x-rays used in medical sciences, laser probing of atmospheric particles, and are all included. The target can be as big as the earth, the moon and other planets, or as small as biological cells that can only be seen through microscopes.

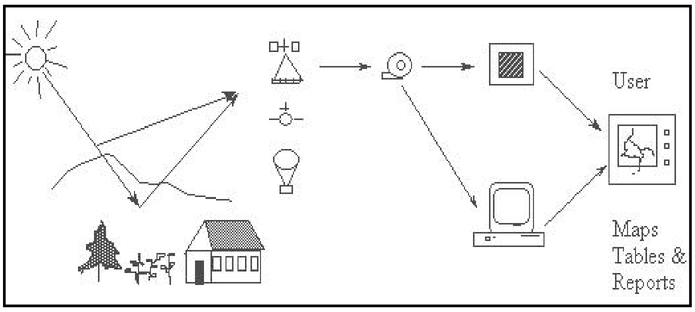

Fig. 1: Flows of Energy and Information in Remote Sensing

III. Major Divisions of Spectral Wavelength Regions

The wavelength of electromagnetic energy has such a wide range that no instrument can measure it completely.

Different devices, however, can measure most of the major spectral regions. The division of the spectral wavelength is based on the devices, which can be used to observe particular types of energy, such as thermal, short-wave infrared and microwave energy. In reality, there are no real abrupt changes on the magnitude of the spectral energy.

The optical region covers 0.3 - 15 mm where energy can be collected through lenses. The reflective region, 0.4 - 3.0 mm, is a subdivision of the optical region. In this spectral region, we collect solar energy reflected by the earth surface. Another subdivision of the optical spectral region is the thermal spectral range, which is between 3 mm to 15 mm, where energy comes primarily from surface emittance.

Table 1: Major uses of some spectral wavelength regions.

Wavelength	Use	Wavelength	Use
G ray	Mineral	1.55-1.75 µm	Water content in plant or soil
X ray	Medical	2.04-2.34 µm	Mineral, rock types
Ultraviolet (UV)	Detecting oil spill	10.5-12.5 µm	Surface temperature
0.4-0.45 µm	Water depth, turbidity	3 cm - 15 cm	Surface relief, soil moisture
0.7-1.1 µm	Vegetation vigor	20 cm - 1 m	Canopy penetration, woody biomass

IV. Resource set-1 (IRS P6) And Its Sensores

The main objectives of IRS-P6 mission are: To provide continued

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remote sensing data services on an operational basis for integrated land and water resources management at micro level with enhanced multi-spectral and spatial coverage with stereo imaging capability. To further carry out studies in advanced areas of user applications like improved crop discrimination, crop yield, crop stress, pest/disease surveillance, disaster management and urban management.

Specification: IRS-P6 is a three axes body-stabilized spacecraft launched by PSLV-C5 into a Sun Synchronous Orbit at an altitude 817 Km. descending node. And repetevity 341 orbits / cycle (24 days). The spacecraft is designed for a nominal mission life of five years. IRS-P6 carries three optical cameras as payload.

Sensors of RESOURCESET-1 (IRS p6):

(i) Linear Imaging Self Scanning Sensor (LISS-IV) Camera

LISS-IV is a high-resolution multi-spectral camera operating in three spectral bands 0.52 to 0.59 m (Green (band 2)), 0.62 to 0.68 m (Red (Band 3)) and 0.76 to 0.86 m (NIR (Band 4)). LISSIV provides a ground resolution of 5.8 m (at Nadir) and can be operated in either of the two modes. In the multi-spectral mode (Mx), a swath of 23.9 Km (selectable out of 70 Km total swath) is covered in three bands, while in mono mode (Mono), the full Swath of 70 Km can be covered in any one single band, which is selectable by ground command (nominal is B3 – Red band). The LISS-IV camera can be tilted up to ± 26° in the across track direction thereby providing a revisit period of 5 days.

(ii)Linear imaging self-scanning sensor

The LISS-III camera is identical to the LISS-III flown in IRS-1C/1D spacecraft except that the spatial resolution of SWIR band (B5) is also 23.5 m (same as that of B2, B3, and B4). LISS-III covers a swath of 141 Km in all the 4 bands.

(iii)Advanced Wide Field Sensor (AWiFS)

AWiFS camera is an improved version compared to the WiFS camera flown in IRS-1C/1D. AWiFS operates in four spectral bands identical to LISS-III, providing a spatial resolution of 56 m and covering a swath of 740 Km. To cover this wide swath, the AWiFS camera is split into two separate electro optic modules, AWiFS-A and AWiFS-B. The IRS-P6 spacecraft mainframe is configured with several new features and enhanced capabilities to support the Payload operations.

V. Processing of Satellite Images

Satellites and airborne sensors are a constant source of images catering a wide range of needs from land-use resource mapping to weather prediction and from target identification to environmental monitoring. The two major issues involved in satellite image processing are -

(a) The early processing techniques specific to the image acquisition system of satellite and airborne sensors and the atmospheric medium through which remotely sensed images are captured.

(b) The computer-based interpretation. The latter, however, involves integration of information extracted from the images with the land-based information and ground truths such as land-use maps, toposheets and vegetation information and so on. Processing of satellite imagery takes a major share of entire image processing activities because of many important applications such as natural resources management, crop estimation, rescue planning and monitoring, environment monitoring.

VI. Neural Network

Neural Networks is a new branch of AI, that enabled a crude simulation of the structure of human brain electronically or in software. The inherent properties of human brain enable it to analyze complex patterns consisting of a number of elements, those individually reveal little of the total pattern, yet collectively represent easily recognizable objects. The concepts of Neural Networks have been motivated right from its inception, by the recognition that the human brain computes in an entirely different way from the conventional digital computers.

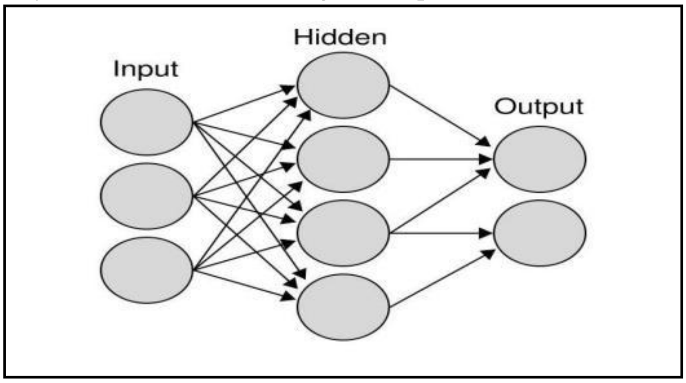

Fig.2: A Neural Network Model

VII. Training of Artificial Neural Networks

We can categorize the learning situations in two distinct sorts. These are:

(i) Supervised learning or Associative learning

In which the network is trained by providing it with input and matching output patterns. These input-output pairs can be provided by an external teacher, or by the system which contains the neural network (self-supervised).

(ii)Unsupervised learning

Self-organization in which an (output) unit is trained to respond to clusters of pattern within the input. In this paradigm the system is supposed to discover statistically salient features of the input population. Unlike the supervised learning paradigm, there is no a priori set of categories into which the patterns are to be classified.

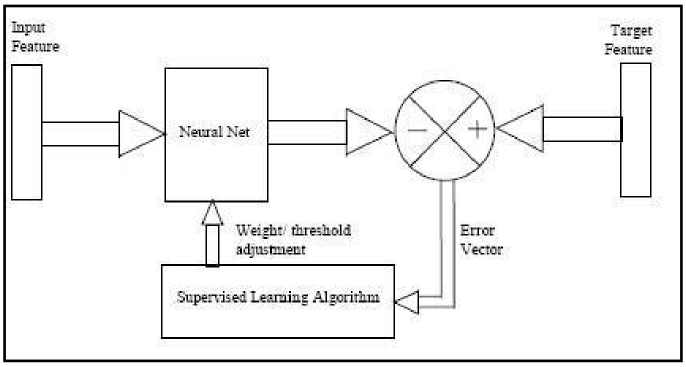

Fig.3 : The Supervised Learning Algorithm

VIII. BPN

Backpropagation is the generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors in an appropriate way as defined by you. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities.

IX. Levenberg-Marquardt (Trainlm)

Like the quasi-Newton methods, the Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as:

$\mathbf{H = J^TJ}$

and the gradient can be computed as:

$\mathbf{g = J^Te}$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$\mathbf{X_{k+1} = X_k - [\, J^TJ+\mu I]^{-1} JTe}$

There are several algorithm characteristics that can be deduced from the experiments described. In general, on function approximation problems, for networks that contain up to a few hundred weights, the Levenberg-Marquardt algorithm will have the fastest convergence. This advantage is especially noticeable if very accurate training is required. In many cases, trainlm is able to obtain lower mean square errors than any of the other algorithms tested. However, as the number of weights in the network increases, the advantage of trainlm decreases. In addition, trainlm performance is relatively poor on pattern recognition problems. The storage requirements of trainlm are larger than the other algorithms tested. By adjusting the mem_reduc parameter, discussed earlier, the storage requirements can be reduced, but at the cost of increased execution time.

In BPN, We define an error function (based on the training set) and would like to minimize it by adjusting the weights using hill climbing algorithm. The error is difference between the target (*t*) and actual (*a*) network output and Mean square error of one output neuron over all *n* examples:

$$MSE=\underline{1}\sum^{n} e(k)^2 = \underline{1}\sum^{n}(t(k) - a(k))^2$$

X. Material and Methods:

A. Satellite View of Bareilly City:

We have satellite images of the Bareilly city region from Google earth, these all images are of high resolution and lies in the visible band. We have taken these images to find the latitudes and longitudes of the survey locations correctly and to show that our analysis is close to reality.

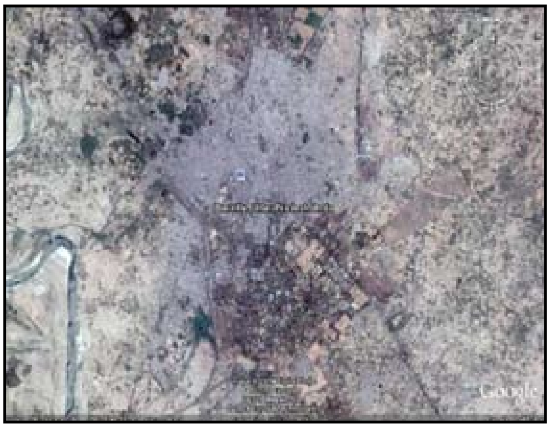

Fig.4 : A Satellite view of Bareilly city

Analysis of Multispectral Image:

a. Assembling the Training Data

We have multispectral image as shown in the fig.3 and by using the Data Cursor tool in the MATLAB we have obtained the R-G-B components of the pixels which best represent the different features of the image.

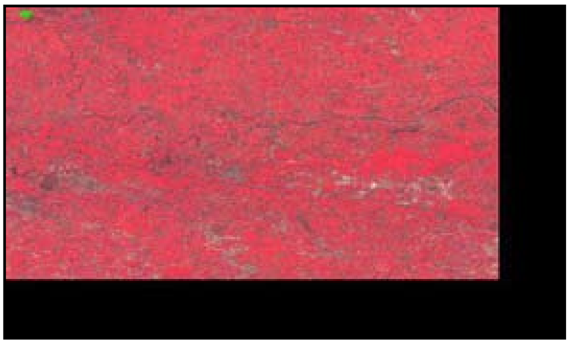

Fig.5 : Multispectral Image

B. Create the Network Object

Now we define the network and specify its features like no. of neurons, range of the values of the input neurons, no. of layers etc. and specify the input and target matrices. In target matrix, there is a particular color for the particular feature to generate the FCC.

Function used to create the neural network is-

net=newff([0 255; 0 255; 0 255],[3 3 3]);

C. Trained the Network

We trained the neural network to find the FCC image from the multispectral image.

Function used to train the network with given set of input and target is-[net,tr]=train(net,p,t);

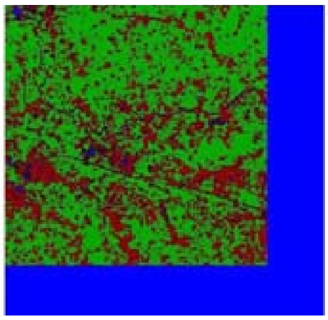

Fig.6: False Colour Composite Image R-G-B components is extracted from False Composite Colour (FCC) image which shows

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area covered by structures, vegetation and water.

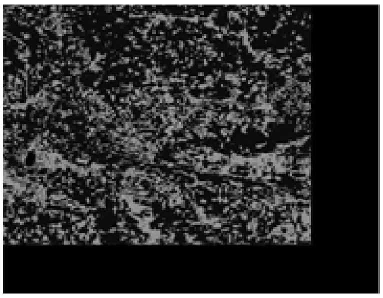

Fig.7(a): R-Component (structures)

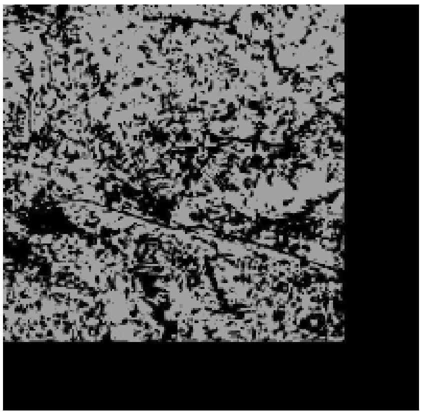

Fig.7(b) : G-Component (vegetation)

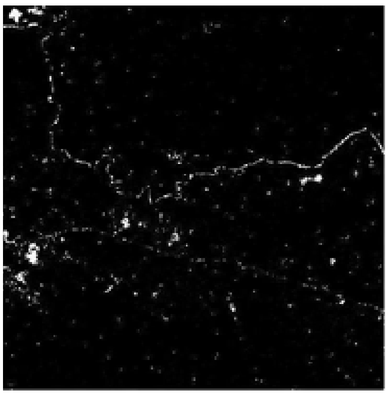

Fig.7(c) : B- Component (Water)

XI. Result

The ANN gives very good result for all the three feature presented here in the multispectral image and almost all the pixels are trained in this case.

Features	No. of pixels	Area covered
Structures	67620	38.33%
Vegetation	86940	49.26%
Water	21840	12.38%

Accuracy of results:

Features	Stru-ctures	Vege-tation	Water	accuracy
Structures	67620	6380	368	90.02%
Vegetation	7941	86940	941	89.78%
Water	1548	169	21840	92.2%

XII. Conclusions

In this paper, ANN is introduced to land cover classification with combination of remote sensing data. Above results show that ANN have good generalization ability on land cover classification and result of using remote sensing data together with geographical ancillary data is better than that of single remote sensing data. In conclusion, multisource land cover classification based ANN could gain higher classification accuracy.

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