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# Comparative Analysis and Classification of Multispectral Remote Sensing Data

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***Abstract*:— The objective of this paper is to utilize the features obtained by the artifical neural network rather than the original multispectral features of remote-sensing images for landcover classification. WT provides the spatial and spectral characteristics of a pixel along with its neighbors and hence, this can be utilized for an improved classification. 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. Here multi-spectral remote sensing data is used to find the spectral signature of different objects.**

Key Words: Remote sensing, Spectral wavelength, Multi-spectral images, ANN

## 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. Complexities in classification of land cover regions of remote sensing images increases because of poor illumination quality and low spatial resolution of remotely placed sensors and rapid changes in environmental conditions. Multispectral remotely sensed images comprise information over a large range of frequencies at different regions, which needs to be estimated properly for improved classification [1]. Many classification systems detect object classes only using the spectral information of the individual pixel ignoring its spatial dependencies. Such approaches may be reasonable if spatial resolution is high or when the spectral intensities are well separated for different classes, which are rarely found in any real life data [4]. Wavelet transform has received much attention justable [5]. These characteristics of the ANN motivated us to use it for the of hidden features from multispectral remote sensing data. ANN provides the spectral reflective coefficient of the RGB pixels for a multispectral remote sensing data based on the intensity of RGB pixel value.

## 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 cell that can only be seen through microscopes.

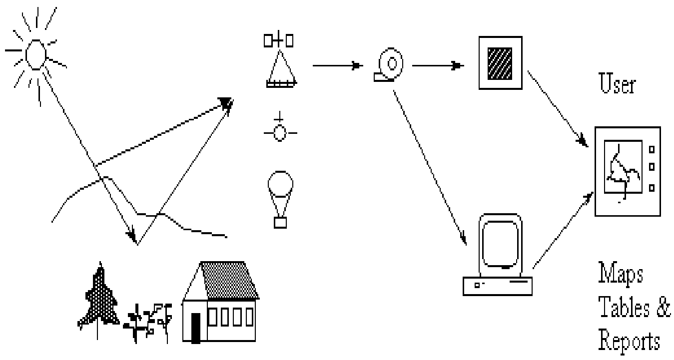


*Fig 1*: Flows of Energy and Information in Remote Sensing

## III. EMPLOYING ARTIFICIAL NEURAL NETWORK

Perhaps the greatest advantage of ANNs is their ability to be used as an arbitrary function approximation mechanism which learns from observed data. However, using them is not so straightforward and a relatively good understanding of the underlying theory is essential.

**Choice of model**: This will depend on the data representation and the application. Overly complex models tend to lead to problems with learning.

**Learning algorithm**: There are numerous tradeoffs between learning algorithms. Almost any algorithm will work for training on a particular fixed dataset. However selecting and tuning an algorithm for training on unseen data requires a significant amount of experimentation.

**Robustness**: If the model,1 cost function and learning algorithm are selected appropriately the resulting ANN can be extremely robust.

With the correct implementation ANNs can be used naturally in online learning and large dataset applications.

## IV. TRAINING OF ARTIFICAL NEURAL NETWORK

A neural network has to be configured such that the application of a set of inputs produces (either direct or via a relaxation process) the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to train the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule.

The learning situations can be categorized in two distinct sorts. These are:

**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).

**Unsupervised learning** 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.

**Reinforcement Learning** This type of learning may be considered as an intermediate form of the above two types of learning. Here the learning machine does some action on the environment and gets a feedback response from the environment. The learning system grades its action good (rewarding) or bad (punishable) based on the environmental response and accordingly adjusts its parameters.

Generally, parameter adjustment is continued until an equilibrium state occurs, following which there will be no more changes in its parameters. The self-organizing neural learning may be categorized under this type of learning.

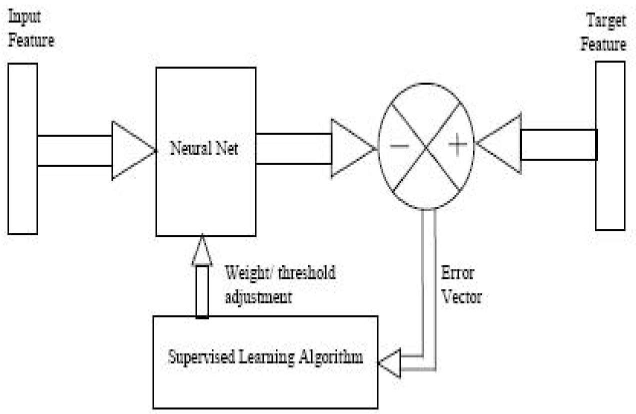


*Fig 2*: The Supervised Learning Algorithm

## V. ANALYSIS OF MULTISPECTRAL IMAGE USING ANN

STEP 1: ASSEMBLING THE TRAINING DATA

As the multispectral image of the Bareilly Ramganga region shown in the figure 5.2 and by using the Data Cursor tool in the MATLAB the R-G-B components of the pixels are obtained which best represents the different features of the image like the River, Water Bodies, Structures, Land and Vegetation as shown:

| Features | R | G | B |
|---|---|---|---|
| **River &Water Bodies** | 120 | 059 | 056 |
| | 128 | 049 | 052 |
| | 131 | 051 | 060 |
| | 136 | 081 | 076 |
| | 142 | 052 | 058 |
| **Structures** | 151 | 104 | 096 |
| | 172 | 093 | 088 |
| | 181 | 059 | 074 |
| | 186 | 074 | 088 |
| | 197 | 098 | 104 |
| | 163 | 052 | 068 |
| | 169 | 096 | 087 |
| | 172 | 074 | 089 |
| | 178 | 062 | 073 |
| **Vegetations and Land** | 224 | 086 | 101 |
| | 229 | 119 | 130 |
| | 230 | 096 | 105 |
| | 234 | 082 | 095 |
| | 240 | 104 | 114 |

*Table 1*:Few of Pixels representing different Features

Thus R-G-B values of almost 100 pixels are obtained and these values may be moulded to form a 3X100 matrix as shown:

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **R:** | 120 | 128 | 131 | 136 | 142 | 151 | 172 | 181 | 186 | 197 | 154 | 163 | 169 | 172.... |
| **G:** | 059 | 049 | 051 | 081 | 052 | 104 | 093 | 059 | 074 | 098 | 049 | 052 | 096 | 074.... |
| **B:** | 056 | 052 | 060 | 076 | 058 | 096 | 088 | 074 | 088 | 104 | 064 | 068 | 087 | 089.... |

*Table 2*:Matrix of Input Pixels

STEP 2: CREATE THE NETWORK OBJECT

Now network is defined and specify its features like number of neurons, range of the values of the input neurons, no. of layers etc. and specify the input and target matrices. Now starts the training of the network and the weights are assigned automatically. Since, the input and output are already defined, the weights for each input-output pair can be developed. Thus, the step 2 makes it to meet the requirement of the mapping relationship between the input and the target.

STEP 3: SIMULATE THE NETWORK RESPONSE FOR WHOLE THE IMAGE

Now, as function representing relation between the input and the target is obtained, then a resulting matrix is generated corresponding to the final FCC of the given image.

But before simulate the image with the help of given network of neurons, multispectral image is convert to the 3-dimensional matrix of dimensions '512X512X3'.

Now this converted form of the multi spectral image applied to neural network for the simulation. After the simulation, a 2-dimensional matrix of the same dimensions is obtained, which is again to be converted into the 3-dimensional matrix of dimensions which represents the FCC corresponding to the given multi spectral image.

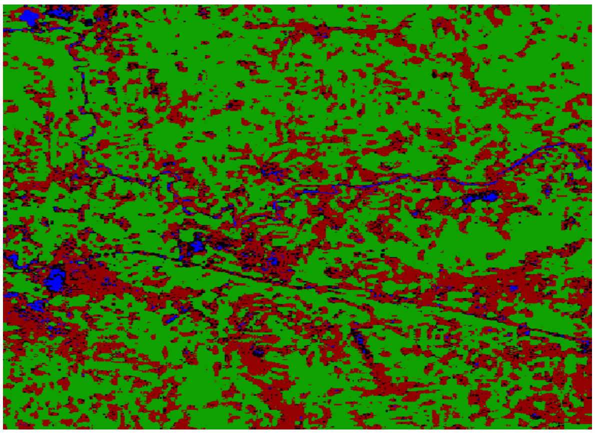

*Fig 3* : FCC Image of the Multi Spectral Image

R-G-B components is extracted from False Composite Colour (FCC) image which shows structures, vegetation and water resources images:

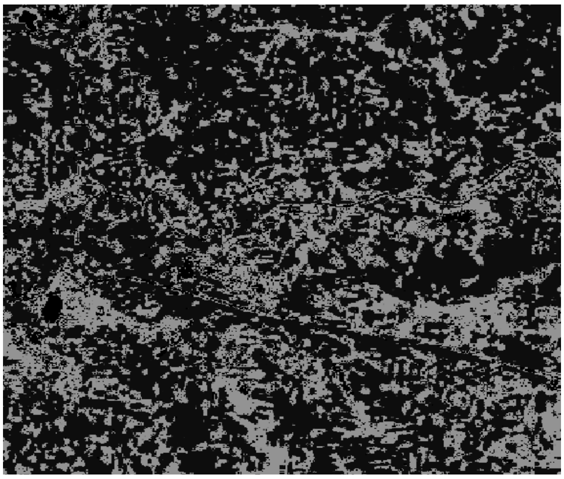

*Fig 4* : R-Component of FCC Image (Structures Image)

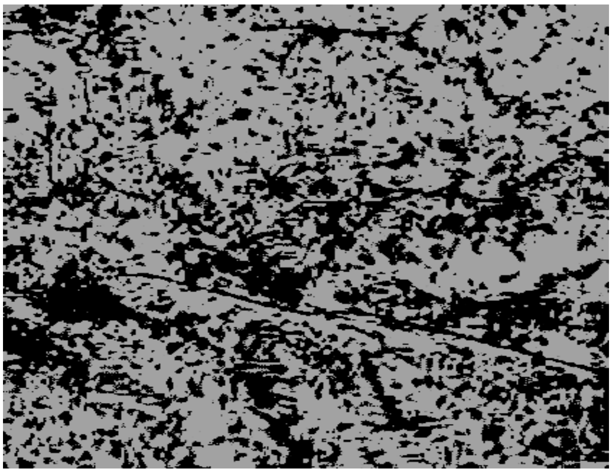

*Fig 5*: G-Component of FCC Image (Vegetation and Land Image)

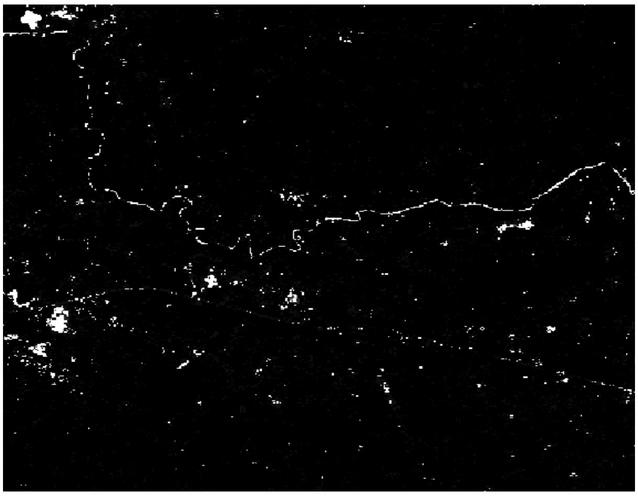

*Fig 6*: B-Component of FCC Image (Water Image)

As now there are three object images structures image, vegetation and land image and water image. From these images number of pixels for different objects are calculated and area coved by different objects and accuracy of results are shown below:

## VI. Accuracy Of Results

*Table 3* : Number of Pixels and Area Covered for Different Object

| Features | No. of pixels | Area covered |
|---|---|---|
| Structures | 67620 | 38.33% |
| Vegetation and Land | 94940 | 53.82% |
| Water | 13840 | 7.84% |

*Table4*: Accuracy of Results for Different Object

| Features | Structure | Vegetationand Land | Water | Accuracy |
|---|---|---|---|---|
| Structure | **67620** | 6380 | 368 | 90.02% |
| Vegetation and Land | 8971 | **94940** | 973 | 89.52% |
| Water | 219 | 891 | **13840** | 91.97% |

## Conclusions

Strictly speaking, Remote Sensing is a newly growing technology; however in only a few years of existence as a theory of their own, it has shown great potential and applicability in many fields. As results are examined, which obtained from the algorithms applied on the multispectral image, it is found that ANN based image classifier method has all the very good results for all the features presented here in the multispectral image. The proposed method explores the possible advantages of using ANN to extract features from images. The improvement in performance of the classification scheme is verified. Of course there are some things needed to be improved on. Accuracy of Classification in the boundaries between different land types can be increased by using much higher resolution and hyper spectral images.

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