ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 7, July 2013

A Neural-Wavelet Based Image Classification for Feature Extraction of a Multispectral Remote Sensing Data

Mohit Kumar[1], Jatinder Singh[2]

Research Scholar, ECE Department, S.L.I.E.T. Deemed University, Longowal Sangrur Punjab, India[1]

Assistant Professor, ECE Department, S.L.I.E.T. Deemed University, Longowal Sangrur Punjab, India[2]

Abstract- The objective of this paper is to utilize the extracted features obtained by the wavelet transform 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.

Index Terms- Remote sensing, Spectral wavelength, Multi-spectral images Wavelet Transform and 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 because of its ability to examine the signal at different scales that represent properties like frequency and its spatial location in the original image. Hence, the use of these coefficients instead of original pixel value is more justable [5]. These characteristics of the WT motivated us to use it for the extraction of hidden features from multispectral remote sensing data. Wavelet provides the spectral reflective coefficient of the RGB pixels for a multispectral remote sensing data based on the intensity of RGB pixel value. WT based 2D image decomposition is used to decompose the multispectral image which provides a measure of information of the image for each level. From the WT coefficients, the corresponding reconstructed images are obtained using the inverse WT, which represent the extracted features of the original image.

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.

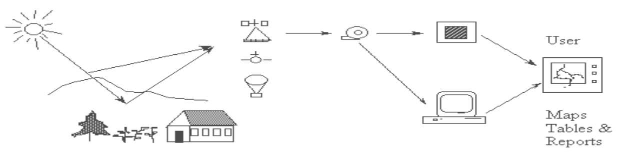

Fig.1 Flows of Energy and Information in Remote Sensing

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 7, July 2013

A. 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 [9]. As Table lists major uses of some spectral wavelength regions.

TABLE I. LISTS OF MAJOR USES OF SOME SPECTRAL WAVELENGTH REGIONS

Wavelength	Use	Wavelen-gth	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

B. RESOURCESET-1 (IRS P6) and its Sensors

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

***1)* 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.

2) Sensors of RESOURCESET-1 (IRS p6)

***a)* 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.

***b)* 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.

***c)* 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.

C. 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 –

1. 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.

2. 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.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 7, July 2013

III. WAVELET TRANSFORM FOR IMAGE DECOMPOSITION

A wavelet [6] is a wave shaped function having a limited length with a zero mean value. This means that a wavelet decreases fast enough in the frequency domain, and that

$$\hat{\psi}(0) = \int \psi(x)dx = 0$$

The wavelet transform of a continuous time signal is a function of scale and shift. A scale as used in the wavelet transform is roughly related to the inverse frequency—small scale implies large frequencies and vice versa.
In wavelet transform, all the wavelet functions related to a single wavelet called the mother wavelet, from which all the wavelet functions are obtained by dilation and contraction.
Wavelets can be realized by iteration of filters with rescaling. The resolution of the image, which is a measure of the amount of detail information in the image, is determined by the filtering operations, and the scale is determined by up sampling and down sampling (sub sampling) operations [8].
The DWT is computed by successive low pass and high pass filtering of the discrete time-domain as shown in fig 2. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous time multi resolution to discrete-time filters. In the figure, the image is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G0 while the high pass filter is denoted by H0. At each level, the high pass filter produces detail information; d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n].

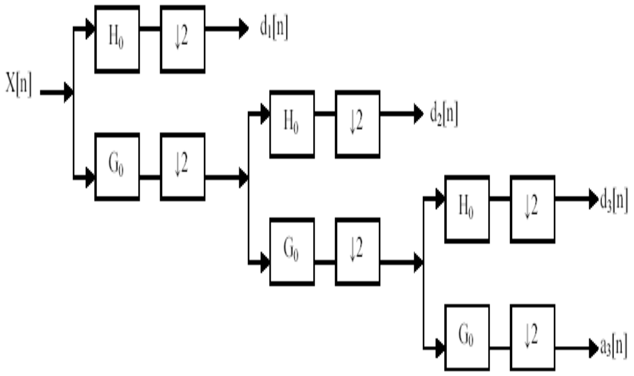

Fig.2 Three-level wavelet Decomposition Tree

At each decomposition level, the half band filters produce image spanning only half the frequency band. This doubles the frequency resolution as the uncertainty in frequency is reduced by half [11]. In accordance with Nyquist's rule if the original signal has a highest frequency of ω, which requires a sampling frequency of 2ω radians, then it now has a highest frequency of ω/2 radians. It can now be sampled at a frequency of ω radians thus discarding half the samples with no loss of information. This decimation by 2 halves the time resolution as the entire image is now represented by only half the number of samples. Thus, while the half band low pass filtering removes half of the frequencies and thus halves the resolution, the decimation by 2 doubles the scale. With this approach, the time resolution becomes arbitrarily good at high frequencies, while the frequency resolution becomes arbitrarily good at low frequencies. The filtering and decimation process is continued until the desired level is reached [10]. The maximum number of levels depends on the size of image. The DWT is then obtained by concatenating all the coefficients a[n] and d[n], starting from the last level of decomposition.

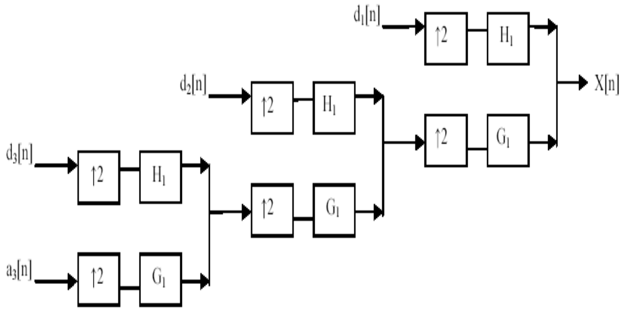

Fig.3 Three-Level Wavelet Reconstruction Tree

Fig.3 shows the reconstruction of the original image from the wavelet coefficients. Basically, the reconstruction is the reverse process of decomposition. The approximation and detail coefficients at every level are up sampled by two, passed through the low pass and high pass synthesis filters and then added [7] [9]. This process is continued through the same number of levels as in the decomposition process to obtain the original image. The Mallat algorithm works equally well if the analysis filters, G0 and H0, are exchanged with the synthesis filters, G1 and H1.

IV. 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.

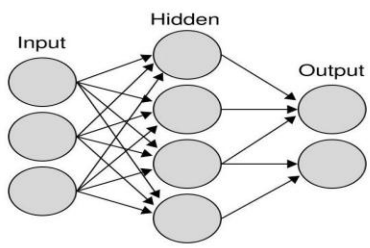

Fig.4 A Neural Network Model

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 7, July 2013

***A.* Training of Artificial Neural Networks:** We can categorize the learning situations in two distinct sorts. These are:

***1)* 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).

***2)* Unsupervised learning** or 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.

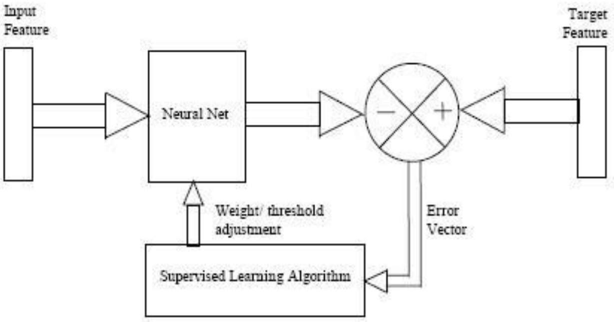

Fig.5 The Supervised Learning Algorithm

V. MULTISPECTRAL IMAGES FROM LISS 4 MX SENSOR

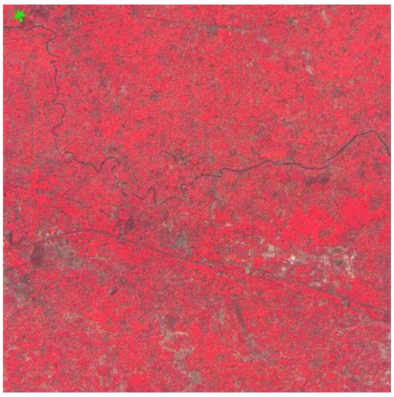

Fig.6 Multi Spectral Image of Bareilly City

VI. ANALYSIS OF MULTISPECTRAL IMAGE USING DWT

Step 1 In very first step the dwt is applied on the multi spectral image for image decomposition as result it returns four decomposed component after 1D decomposition as shown:

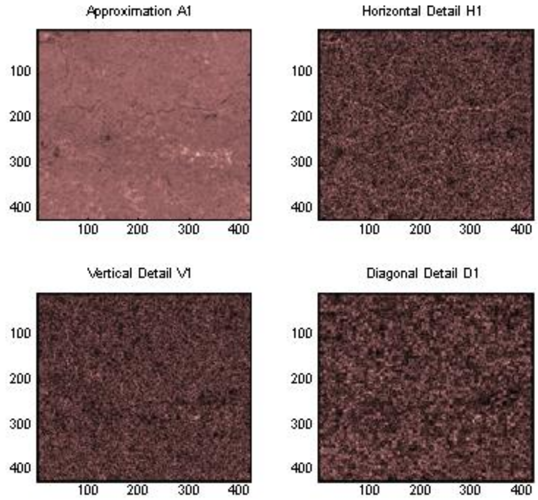

Fig.7 1D Image Decomposition

Step 2 Again dwt is applied on approximated detailed component A1 for 2D image decomposition. After 2D decomposition IDWT is used for the reconstruction of original multispectral image.

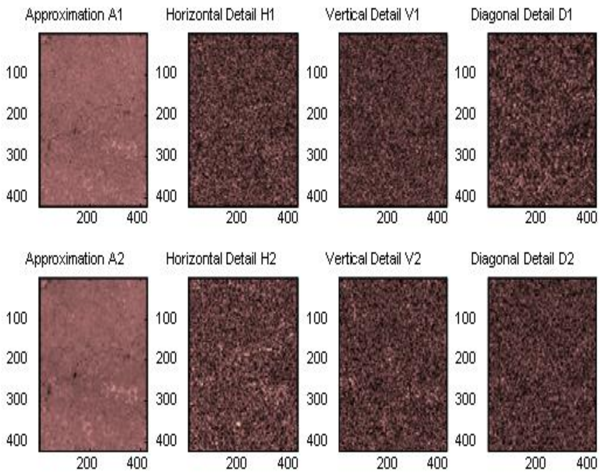

Fig. 8 2D Image Decomposition

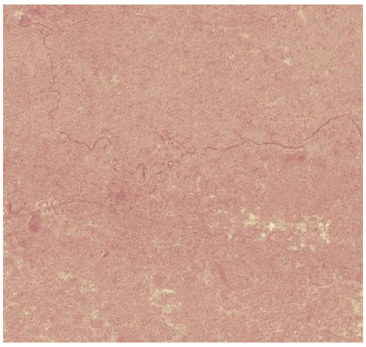

Fig.9 Original Reconstructed Multispectral Image

Step 3 Now ANN is applied for the feature extraction of the reconstructed multispectral image for which input data is assembled using the Data Cursor tool in MATLAB. The R-G-B components of the pixels are obtained which best represent the different features of the image.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 7, July 2013

Step 4 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]);

Step 5 Then network is trained 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);

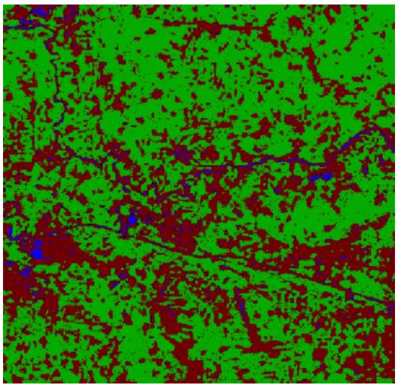

Fig.10 FCC image for Original reconstructed Multispectral Image

Step 6 R-G-B components are extracted from False Composite Colour (FCC) image which shows structures, vegetation and water resources images:

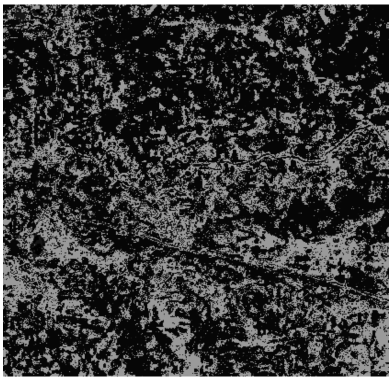

Fig.11 R-component of FCC image (Structures Image)

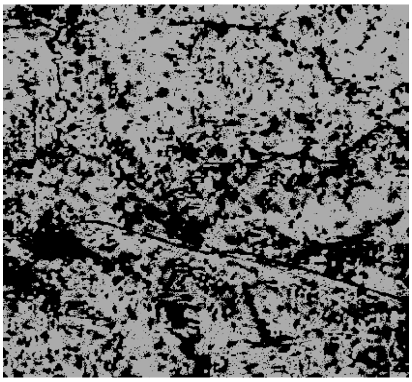

Fig.12 G-component of FCC Image (Vegetation and Land Image)

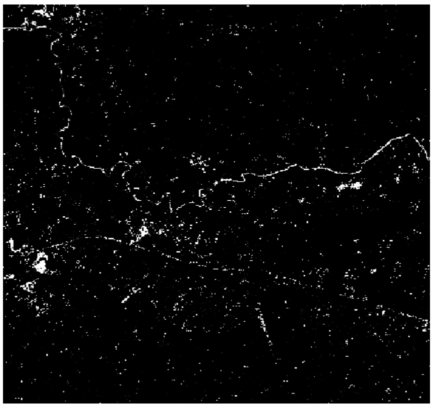

Fig.13 B-component of FCC image (Water Image)

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

TABLE II. NUMBERS OF PIXELS AND AREA COVERED FOR DIFFERENT OBJECT

Features	Structures	n and Land	Water	accuracy
Structures	**64059**	3680		93.82%
Vegetation and land	4783	**96902**	487	4.56%
Water	317	503	**15439**	94.69%

TABLE III. ACCURACY OF RESULTS FOR DIFFERENT OBJECT

Features	No. of pixels	Area covered
Structures	64059	36.31%
Vegetation and land	96902	54.93%
Water	15439	08.75%

VII. CONCLUSION

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 WT 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 WT 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.

ISSN (Print) : 2319-5940
ISSN (Online) : 2278-1021

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 2, Issue 7, July 2013

VIII. REFERENCES

1. Saroj K. Meher, B.Uma Shankar, and Ashish Ghosh, 2007, "Wavelet Feature Based Classifiers for Multispectral Remote-Sensing Images", Indian Statistical Institute, Kolkata, India.
2. Pai-Hui Hsu Yi-Hsing Tseng, 2002, "Feature Extraction of Hyperspectral Data Using the Best Wavelet Packet Basis" IEEE Page(s):1667-1669.
3. B. Uma Shankar, Saroj K Meher and Ashish Ghosh, 2007, "Neuro-Wavelet Classifier for Remote Sensing Image Classification", Proceedings of the International Conference on Computing: Theory and Applications (ICCTA), Indian Statistical Institute, India.
4. Yikuan Zhang, Ke Lu, and Ning He and Peng Zhang, 2007, "Research on Land Use/Cover Classification Based on RS and GIS", Second International Symposium on Plant Growth Modeling, Simulation, Visualization and Applications, China.
5. Yan Guo, Lishan Kang, Fujiang Liu, Huashan Sun and Linlu Mei, 2007, "Evolutionary Neural Networks Applied to Land-cover Classification in Zhaoyuan, China" Proceedings of the 2007 IEEE Symposium on Computational Intelligence and Data Mining, Page(s): 499-503.
6. Yoshikazu Iikura, 2007, "Landcover Classification of Satellite Imagery with Tesselated Spatial Structure Model" IEEE, Page(s):1463-1467.
7. Idan FELDBERG, Nathan S. NETANYAHU and Maxim SHOSHANY, 2002, "A Neural Network-Based Technique for Change Detection of Linear Features and Its Application to a Mediterranean Region" IEEE Page(s):1195-1197.
   W.Zou, Z.Chi and K.C.Lo, 2008, "Improvement of image classification using wavelet coefficients with structured based neural network", International Joint Conference on Neural Networks Sheraton Vancouver Wall Centre Hotel, Vancouver, BC, Canada.
8. Chih-Cheng Hung, Youngsup Kim and Tommy L. Coleman, 2010, "A Comparative Study of Radial Basis Function Neural Networks and Wavelet Neural Networks in Classification of Remotely Sensed Data", U.S.A.
9. Xia Jun, Liu Jinmei, Wang Guoyu, and Li Jizhong, 2011, "The Classification of Land Cover Derived from High Resolution Remote Sensing Imagery".
10. Weibao ZOU, Wai Yeung YAN and Ahmed SHAKER, 2012, "Neural Network Based Remote Sensing Image Classification in Urban Area", WCCI IEEE World Congress on Computational Intelligence.