International Journal of Science and Research (IJSR)
ISSN: 2319-7064
SJIF (2019): 7.583

Insight into Remote Sensing and Algorithms to Study the Patterns in Universe

Tutu Sengupta[1], Shagun Sengupta[2], Satish J Sharma[3]

[1]Maharashtra Remote Sensing Application Centre, Nagpur, India
Email: *t.sengupta[at]mrsac.gov.in*

[2]Royal Philips N.V
Email: *shagunsengupta2804[at]gmail.com*

[3]Department of Electronics, RTM Nagpur University, Nagpur, India
Email: *sharmasat[at]gmail.com*

Abstract: ***Patterns are an integral part of the universe. There are several algorithms designed to extract information about the objects. These algorithms can be modified/ combined or written anew so that the patterns can be recognized from chaos. Another important part of deciphering patterns is the method for gathering information about it. This can be done using various geospatial technologies like remote sensing using satellite data, LiDAR, SONAR, DRONES etc. Better and timely availability of the data helps to study the patterns on earth and the changes over a period of time using temporal or multidate data. This paper investigates the basic of remote sensing technology and the various patterns recognition techniques which can be used to extract information from the patterns.***

Keywords: Remote sensing, pattern recognition, hard classification, soft classification, fuzzy classification

1. Introduction

Patterns exist everywhere in the universe. Patterns of the celestial bodies and their trails in the sky, patterns of the migratory birds or the swans flying in the sky, patterns in the leaves, the fruits and flowers, patterns that the drainages make on the earth as seen on satellite data, patterns of urban and rural areas, patterns of transport network, patterns of clouds forming to bring rains or turning into cyclones, patterns in numbers like the Fibonacci series. All these patterns are clearly discernable with the study using various methods. There is abundant scope to apply the algorithms in computer science to study these patterns and use them to identify similar ones and model their cause and effects. There is a huge scope to improve upon the already available algorithms and devise new ones for better understanding and delineation of the earth features or those in the universe. In this article and attempt has been made to give a detailed insight into the various techniques like remote sensing to study the patterns on earth as well as the techniques which can be used to delineate these patterns using computer based recognition techniques.

2. Remote Sensing

Remote Sensing (RS) is the technique of gathering information about an object without coming into contact with it[1]. According to White *et al*[2]., remote sensing is a collection of all methods of capturing pictures and other forms of electromagnetic energy, either reflected, transmitted, scattered, from earth's surface, from a distance. The process of seeing the object by human eye, sonar sounding by the bats, sonar sounding of the sea floor, ultra sound techniques used in medical science and industry, magnetic resonance imaging (MRI), x- rays used in medical science, laser probing of the atmospheric particles, are all examples of remote sensing applications. The target can be as big as the Earth and other planets or as small as the biological cells of the body. According to the United Nations, Remote Sensing (RS) means: sensing of earth's surface from space by making use of the properties of electromagnetic wave emitted, reflected or diffracted by the sensed objects, for the purpose of improving natural resource management, land use and environmental protection. According to James B.Campell[3], remote sensing is the practice of deriving information about the earth's land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiations in one or more regions of the electromagnetic spectrum, reflected or emitted from the earth's surface.

The basic requirement of RS is a source of energy to illuminate the target (unless the target itself is emitting energy). The source of energy is in the form of electromagnetic radiation (EMR). Figure 1 shows the EM spectrum, ranging from the shorter wavelengths like gamma rays and x-rays to longer wavelengths like the microwaves and the radio waves.

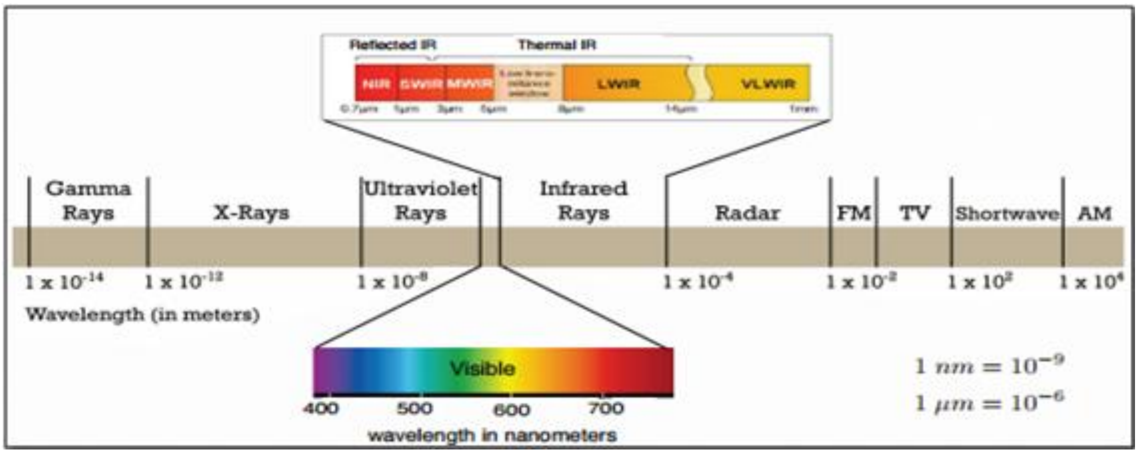

Figure 1: Electromagnetic Spectrum

(Source: Dr. Gülşen Taşkın Kaya, ITU Institute of Earthquake Engineering and Disaster Management June, 2014)

There are several regions of the EM spectrum useful for monitoring the Earth's resources through remote sensing. As seen in Figure 1.1, the *visible range* covers a small portion of the very large spectrum i.e., from 0.4μ m-0.7 μ m. To know the distribution of the various objects on Earth and to inventory, monitor and manage the resources, both natural and manmade, it is essential to use satellite remote sensing, as it is very effective way of gathering information of the Earth surface. The data from the remotely sensed imagery can be used for information extraction to identify the spatial and temporal distribution of various targets of interest. Each earth feature manifests with a unique pattern. The urban and rural areas, water bodies, rivers, forests, agricultural field, mining areas, wastelands, deserts, hills and mountains, snow clad etc., each has its own pattern manifested on the earth surface.

2.1 Remote Sensing Data Acquisition

Remote sensing data acquisition can be done using various platforms like satellite, aircrafts, balloons, rockets, space shuttles, cherry pickers etc[1]. Sensors are mounted on these platforms to collect the data. The sensors include aerial photographic cameras, non-photographic instruments, such as radiometers, electro-optical scanners, radar systems etc. The amount of energy that is sensed by the sensor from the platform is also a function of the resolution and the sampling frequency. Resolution can be stated as the maximum separating or discriminating power of an instrument. Remotely sensed data has four types of resolution viz., Spatial, Spectral, Temporal and Radiometric.

Spatial resolution is the ability to separate features, *spectral resolution* gives the location, width and sensitivity of the chosen wavelength bands, *radiometric resolution* gives the depth of information and *temporal resolution* gives the time between observations.

Remote sensing is done in the various regions of EMR (wavelength regions) like:
(i) Visible and Near Infrared region of EMR
(ii) Thermal Infrared region of EMR
(iii) Microwave region of EMR

The remote sensing sensors are stationed above the earth surface at a distance of 700 to 900 km. The gases in the atmosphere interact with the EMR resulting in varying degree of transmission, absorption, emission and/or scattering from the atmospheric molecules which is a function of wavelength (λ).Before the EMR reaches the earth's surface, it has to travel a significant distance in the earth's atmosphere. The particles and gases in the atmosphere interact with the radiation, and cause scattering, reflection, transmission and absorption. Scattering occurs when the particles or the large gas molecules present in the atmosphere interact with EMR. The amount of scattering depends on the wavelength of radiation. There are three types of scattering:

(i) *Rayleigh Scattering* occurs when the particles are very small compared to the wavelength of radiation. These particles could be specks of dust, nitrogen or oxygen molecules. Rayleigh scattering causes shorter wavelengths to be scattered more than the longer wavelengths. It is the dominant in the upper atmosphere.
(ii) *Mie Scattering* takes place when the particles in the atmosphere are the same size as the wavelength of radiation. Dust, pollen grains, smoke and water vapour cause this and the longer wavelengths are more affected. Mie scattering occurs in the lower portions of the atmosphere.
(iii) *Non-selective scattering* occurs when the particles are much larger than the wavelength of radiation. Water droplets and large dust particles can cause this type of scattering. This type of scattering causes all types of wavelengths to be scattered equally. The manifestation causes fog and clouds to appear white to our eyes.

The gasses in the atmosphere allow certain radiations to pass through it, phenomena called as transmissivity. The gases in the atmosphere absorb radiation in certain wavelength while allowing radiation with differing wavelengths to pass through. The wavelength regions in the EMR that are absorbed by atmospheric gases such as water vapour, carbon dioxide, ozone form absorption bands. For these absorption bands, the transmission values are very low. In contrast to the absorption bands, are the regions in EMR, for which the wavelengths can easily pass through the atmosphere or the atmosphere is transparent. These wavelength bands are known as ***atmospheric windows***. Most remote sensing instruments work in these wavelength regions.

For the effective use of the remote sensing-based data it is essential to develop accurate and fast pattern recognition procedures and techniques to be able to extract information based on requirement of the project.

2.2. Characteristics of remotely sensed data:

Satellite imagery consists of images of Earth collected by satellites. The characteristics of a remotely sensed image basically depend on the nature of the corresponding sensor. These sensors can be placed on balloons, airplanes and satellites and are called platforms.

Remote sensing satellites used for observing Earth features have sensors which can be broadly categorized as *passive sensors* and *active sensors*[2].The passive sensors use other sources of light like sun light as in case of a normal photograph using a camera while in active sensors, the satellite uses light from its own source similar to using the flashlight. When EMR falls on any Earth feature, several types of interactions take place such as scattering, reflection, refraction, transmittanceetc[1].These are then detected by the sensors onboard the satellite. Passive sensors directly receive the radiance generated by the observed ground area by reflecting part of the incident solar radiation[2, 3]or those spontaneously emitting electromagnetic radiations according to the Planck's law [3, 4].

On the other hand, an active sensor transmits an electromagnetic pulse (usually, a microwave signal with frequency around 10 GHz) and receives the resulting echo signal backscattered by an illuminated ground area[4].In the recent past, the rapid development of the sensor technology has seen a great improvement in the resolutions - spatial resolution has now got a wide range from 1 km to 30 cm, spectral resolution has increased from the traditional blue, green, red and infrared to hyperspectral imageries with almost 200 to700 channels (AVRIS and HYPERION) in a small range of frequencies, revisits (temporal resolution) has increased from once in 18 or23 days to even 12hours (COSMO/SkyMed SAR constellation or by "Pleiades") due to capability of data sharing amongst various satellites and their constellations and also with the facility to tilt the cameras/ sensors on board the satellite. Similarly, the radiometric resolution has changed from 8 bits to 16 bit or 32 bits.

The availability of such high-resolution data increases potentialities of remote-sensing imagery for Earth resources inventory, monitoring and assessment. This can be made possible only with the use of image processing algorithms. The basic steps involved are data acquisition, data transmission to ground station, data pre-processing, image analysis and information extraction and transmission to end user.

During the image-acquisition phase, sensors acquire data over the area of interest and transmit them to a set of ground receiving stations. The resulting data require several pre-processing operations before being useful for information extraction purposes. Automatic or semi-interactive calibration, defocusing, radiometric and/or geometric correction procedures have to be applied to correct data for radiometric, atmospheric, and/or geometric distortions. In addition, geo-referencing procedures (including re-sampling and interpolation) are needed in order to define a one-to-one correspondence between the image coordinates of a given pixel and the geographical coordinates of the related ground area[1, 2]. Through the identification of common and easily identifiable points called Ground Control Points (GCPs), various transformation equations and application of projection parameters.

The image is then subjected to various image extraction and processing techniques using different algorithms, based solely on clustering or using signatures or a priori knowledge of the area of interest. This entire process of training the computer to extract valuable information from image is known as *pattern extraction*. The image so interpreted can be converted into vector format called as map and other similar layers can be overlaid on it to extract composite information in a computer-based system called as Geographic Information System (GIS). Thus, GIS is a computer-based system to capture, store, analyze, update and display data.

3. Spectral signature of Earth Surface Features

"Every natural and artificial object reflects and emits electromagnetic radiation over a range of wavelengths in its own characteristic manner, according to its chemical composition and physical state[5]". Spectral signatures are based on emittance and unique reflectance properties of targets on surface of earth. A spectral signature plots all the variations of reflected EMR as a function of wavelengths. Each object has its own chemical composition and hence its own spectral signature. The spectral signature curve of different materials is shown in the Figure 2[6].

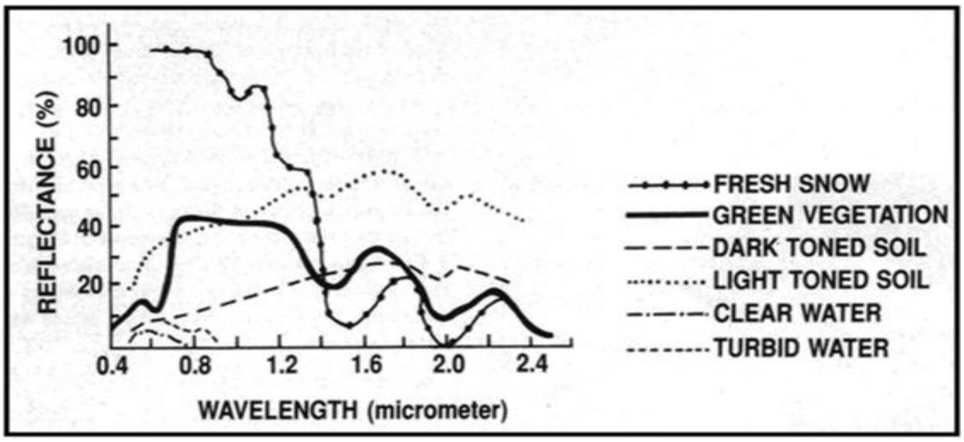

Figure 2: Spectral signature of different Earth features
(Source: National Wetland Atlas of Maharashtra, 2010)

The spectral curve shows that vegetation reflects 40% - 50% of the energy incident on it in the wavelength range of 0.7 to 1.3 µ m. This phenomenon is attributed to the internal structure of leaf. As the internal structure are highly variable amongst the plant species, the reflectance measurement often helps to discriminate among the species. Beyond 1.3µm, energy incident upon vegetation is essentially absorbed or reflected with no transmittance of energy. Again on observing the spectral curve we see that dips in reflectance occur at 1.4µm, 1.9µmand 2.7 µm as water in the leaf absorb strongly in these wavelengths called as water absorption bands. There is reflectance at 1.6 µm and 2.2 µm in the absorption band. In the wavelength ranges beyond 1.3 µm, leaf reflectance is nearly inversely related to the total water present in a leaf and is a function of the both the moisture content and the thickness of the leaf.

The spectral reflectance of soil act over a small range of spectral band. The factors which affect the soil reflectance are moisture content, soil texture (determined by the proportion of sand, silt and clay), surface roughness, presence of iron oxide and organic matter. As in case of vegetation, the presence of moisture in the soil decreases its reflectance especially in the water absorption bands at about 1.4µm, 1.9µm, 2.2µm and 2.7 µm. The soil reflectance pattern is also related to soil texture.

Water absorbs radiation at NIR and beyond (strong absorption bands at 1.4, 1.9 and 2.7 µm). The reflectance from a water body is influenced by the specular reflection from surface of the water body, material suspended in the water or the reflectance from the bottom of a water body. Clear water absorbs relatively little energy with wave lengths less than 0.6 µm, resulting in high transmittance in blue-green portion of the EMR.

In the recent past, reflectance spectra of numerous materials have been measured and published in the field of remote sensing by researchers at the Spectroscopy Lab of USGS[8] and have been compiled as a spectral library. The libraries are used as references for material identification in remote sensing images. The ASTER spectral library is available on website (http://spec.jpl.nasa.gov)[9]. It contains over 2400 spectra of natural and man-made materials. Remote sensing measurements made in situ and from airborne and space borne platforms provide valuable information for research studies. The Advanced Spaceborne Thermal Emission Reflection Radiometer (ASTER) on NASA's Terra platform provides such measurements and has been widely used in geological and other studies. The library includes contributions from the Jet Propulsion Laboratory (JPL), Johns Hopkins University (JHU) and the United States Geological Survey (USGS). The library includes spectra of rocks, minerals, lunar soils, terrestrial soils, manmade materials, meteorites, vegetation, snow and ice covering the visible through thermal infrared wavelength region (0.4 – 15.4 µm).More recently, complimentary spectral libraries have been made available from other collections, like website (http://speclab.cr.usgs.gov)[8]. Christensen *et al.*[10], Clark *et al.*[11], Ducart *et al.*[12], Hellman *et al.*[13], Hubbard *et al.*[14], Rockwell *et al.*[15], Rowan *et al.*[16], Vaughan *et al.*[17, 18], Zhang *et al.*[19] have published extensive literature on spectral signatures in remote sensing.

Using these spectral databases, digital image analysis allows identification of the spectral regions that best separate, ground features of interest and selection of appropriate spectral bands for in-situ data collection. Hyper spectral data is available for use in detailed investigation of various material identification on Earth surface. There are many important uses of hyper spectral data like that for mineral mapping and vegetation identification.

4. Use of multi-temporal satellite data:

Crop type classification in agricultural areas using remote sensing data and forest cover mapping have been employed since more than two decades like many other earth resource applications. However, in an environment like agriculture which is highly variable in time and space, feature identification becomes complicated by only analyzing their spectral properties. Use of multitemporal data may be a solution and a way to take the advantage of the spectral discrepancies over time. Similarly, to find the crown density of forest, multi temporal data may be used for identification of evergreen forest, semi evergreen forests, deciduous forests etc.

Multi temporal data can be extensibly exploited in different ways to improve crop classification. A simple way is to merge two (or more) images from different dates during the growing season to prepare a product for visual interpretation.

A crop calendar provides the knowledge of crop development stages for an area and is helpful to determine the presence of a particular crop at certain date. For an automated classification, the multidate images can be combined to prepare a single product and classification performed. Another method is the use of principal component analysis to reduce the dimensionality of the combined dataset prior to the classification[1].

In the multi temporal data analysis for crop classification, a crop profile can be generated i.e., physical modeling of the time behavior of each crop's spectral response pattern i.e., the phonological development of the crop from seedling emergence to maturity of crop. Hence by relating the observed temporal-spectral pattern to the expected phenological development pattern associated with different crops, a crop identity or label can be assigned to the field.

5. Identifying the patterns in universe using remote sensing and pattern recognition techniques:

Pattern Recognition can be defined as the science and the art of finding meaningful patterns in the data which can be extracted through classification. Duda *et al.*[21]and Tou *et al.*[22] have done pioneering work on pattern recognition techniques. A digital image consists of a two-dimensional array of individual picture elements called pixels. Each pixel represents an area on the Earth's surface and has an intensity value, represented by a digital number. This intensity value is a measure of the energy reflected (or emitted) from the ground[20]. This value is normally an average of the whole ground area covered by the pixel. Resolution of an image is constrained by the pixel size determined by the Instantaneous Field of View (IFOV) of the sensor's optical system. IFOV is a measure of the ground area viewed by a single detector element in a given instance in time. Therefore, more than one land cover type or feature may be included in an IFOV, resulting in mixed pixels. The number of mixed pixels in an image is a function of the IFOV of the instrument and the spatial complexity of the phenomenon being imaged[1].The presence of the mixed pixel can cause the output of any conventional classification system to give erroneous result. The problem of mixed pixel can be solved by sub pixel analysis.

The main objective of image classification is to automatically categorize all pixels in an image into land cover classes. The satellite data can be classified using the supervised (discrimination) method or the unsupervised (clustering) method. The unsupervised approach attempts spectral grouping or clustering that may or may not be as useful to the user as desired. The outputs are in the form of spectral and statistical clusters.

In the supervised classification, the image analyst supervises the pixel categorization process by specifying to the computer algorithm; numerical descriptors of the various land cover types present in the scene. Representative cover types - sample sites of known types, called training areas or training sites, are used to compile a numerical interpretation key that describes the spectral attributes for each feature type. Each pixel in the data set is then compared numerically to each category in the interpretation key and labeled with the name of the category it looks most like.

The basic difference between supervised and unsupervised approaches is that, the user defines useful information categories and then examines their spectral separability whereas in the unsupervised approach, the spectral separability is first determined and then classes are defined. In areas of complex terrain, orwhere the field sizes are less, the unsupervised approach is preferable to the supervised one, as in the supervised approach the user shall have difficulty in selecting training sites due to variability of spectral response within each class. The supervised approach is subjective as the analyst tries to classify information categories, which are often composed of several spectral classes whereas spectrally distinguishable classes will be revealed by the unsupervised approach. Thus, the ground survey in supervised classification approach is more than in the unsupervised approach. Additionally, the unsupervised approach, being unbiased, has the potential advantage of revealing discriminable classes[23].The classes that result from unsupervised classification are spectral classes because they are based solely on the natural groupings in the image values.

The analyst must compare the classified data with some form of reference data (such as larger scale imagery or maps) to determine the identity and informational value of the spectral classes. In the supervised approach, the user defines useful information categories and then examines their spectral separability; in the unsupervised approach we determine spectrally separable classes and then define their informational utility.

There are numerous clustering algorithms that can be used to determine the natural spectral groupings present in data set like the "K-means" approach also called as ISODATA (Interaction Self-Organizing Data Analysis Technique). The algorithm arbitrarily "seeds", or locates, the number of cluster centers in the multidimensional measurement space, as given by the user as input. Each pixel in the image is assigned to the cluster whose arbitrary mean vector is closest. After all pixels have been classified in this manner, revised mean vectors for each of the clusters are computed. The revised means are then used as the basis of reclassification of the image data. The procedure continues (based on number of iterations) until there is no significant change in the location of class mean vectors between successive iterations of the algorithm. Once this point is reached, the analyst determines the land cover identity of each spectral class. Asthe K-means approach is iterative, it is computationally intensive. Therefore, it is often applied only to image sub-areas rather than to full scenes. Supervised classification can be used to samples of known identity to classify pixels of unknown identity. Samples of known identity are those pixels located within training areas. Pixels located within these training samples guide the classification algorithm to assigning specific spectral values to appropriate informational class.

In supervised classification we have a set of data whose characteristics are already known, called the training set or signature file, with class label associated with each of the data. The signatures can be parametric or non- parametric. Parametric signatures are based on statistical parameters like mean, covariance matrix of pixels in a training sample and are useful for the statistically based classifier like Maximum Likelihood Classifier (MXL).A non-parametric signature is not based on statistics, but on discrete objects like polygon or rectangle in an image, which are used to define the boundaries of classes. A non- parametric classifier uses a set of non-parametric signatures to assign pixels to a class based on their location inside or outside the area in feature space.

Multispectral data is the basic input for image classification, and the spectral pattern present within the data for each pixel is used as numerical basis for categorization. That is, different feature types manifest different combination of DNs based on their inherent spectral reflectance and emittance properties. The term classifier refers loosely to a computer program that implements a specific procedure for image classification. Many image classification techniques are available. It has been found that not all the classification techniques are suitable for object discrimination as characteristics of each image and the circumstances for each study vary so greatly[23].

5.1 Soft Classification

Traditional supervised and unsupervised classifications have their disadvantages. In contrast to classic image processing methods, the basic processing units of object-oriented image analysis are image objects or segments and no single pixels [25]. The classification acts on image objects. One motivation for the object-oriented approach is the expected result of most image analysis tasks is the extraction of real-world objects, proper in shape and proper in classification. This expectation cannot be fulfilled by traditional, pixel-based approaches[24]. These traditional classifications produce a characteristic, inconsistent, salt-and- pepper output and are unable in extracting objects of interest. Under the soft classification method, each class, of a classification scheme, contains a description of the class it defines. Each class description consists of a set of fuzzy expression allowing for the evaluation of specific features and their logical operations. The fuzzy set of rules are defined by membership functions that identify those values of a feature that are regarded as having high, low or zero membership respectively of a particular fuzzy set[26].

5.2 Fuzzy Classification

Fuzzy classification helps in dealing with uncertainty and complexities of classification with the concept of fuzzy set. Membership concept in fuzzy classification allows the availability of one entity in more than one class. Hence, in image classification, we can assign a pixel to more than one class or grade and describe in terms of membership grade. Fuzzy classification takes into account the presence of pixels of mixed make up in an image and cannot be assigned to a particular category[4].Fuzzy classification is designed to work using a membership function, wherein a pixel's value is determined by whether it is closer to one class than another class[22]. A fuzzy classification does not have a definite boundary and each pixel can belong to several different classes[4]. Jensen[6] has expressed that thoughhe process of fuzzy classification also demands that the training sites be marked but it is not restricted like that in case of traditional classifiers as in this case mixed pixels can be present. Once the fuzzy classification is done a moving window convolution can be performed. Using the multilayer classification and distance file, the convolution creates a new single class output file by computing a total weighted distance for all classes in the window. Fuzzy Convolution creates a single classification layer by calculating the total weighted inverse distance of all the classes of pixels in a window. Thereafter, it assigns the center pixel in the class with the largest total inverse distance summed over the entire set of fuzzy classification layers. This has the effect of creating a context-based classification to reduce the speckle or salt and pepper in the classification. Classes with a very small distance value remain unchanged while classes with higher distance values may change to a neighboring value if there is sufficient number of neighboring pixels with class values and small corresponding distance values.

5.3 Endmember selection

Pure features in a mixed pixel are referred to as endmembers of that pixel. The selection of end member can be done by two methods:

- From spectral library (field or laboratory) library
- From purest pixel in image

Endmembers obtained from spectral library are generally referred to as 'known' while from the other option are called as derived. Derived endmembers are collected over the known members as they are collected under same atmospheric conditions. It saves from the necessity to atmospherically correct the image and calibrate the data to reflectance space. Also it sets aside the possibility of ignoring a pure endmember in the scene. Fuzzy classification can also be performed as standard image classification, that is, supervised and unsupervised classification. In unsupervised classification, features are classified merely on basis of their spectral characteristics which is generally achieved by some clustering techniques.

Many Researchers have published literature which rejects idea that a pixel can be assigned to a single cover type only[25]-[26]. These sub-pixel procedures attempt to extract components of the pixel, recognizing that more than one land cover type may exist within a pixel. These components of a pixel are referred to as endmembers as they represent the cases where 100 percent of the sensor’s IFOV is occupied by a single homogeneous cover type[1].

6. Conclusion

The whole article is based on the concepts of Physics and Computer Science and deals with the interaction of Electromagnetic Radiation with the Earth’s atmosphere and the objects on Earth. It also showcases some of the methodologies/ algorithms or methods which can be used to study and delineate the earth features or the patterns which exists in the universe. A detailed study of the patterns is exciting and offers a huge scope for further research. The better the understanding better is the scope to separate the pattern from the ‘chaoses.

References

[1] *Remote Sensing and Image Interpretation*, Lilles and T.M. and Kiefer R.W.: John Wiley and Sons, New York, 2001
[2] White J.D., Ryan K.C., Key C.C. and Running S.W.: Remote Sensing of Forest Fire Severity and Vegetation Recovery, *Int. J. Wild Land Fire 6 (3), 125-136 (1996)*
[3] *Introduction to Remote Sensing*, Campbell J.B.: The Guilford Press, New York, 1987
[4] *Introductory Digital Image Processing: A Remote Sensing Perspective*, Jensen, J. R.: 2nd Edn. New Jersey, Prentice-Hall, 1996
[5] *Remote Sensing Tutorial*, *Fundamentals of Remote Sensing*, Canada Centre for Remote Sensing, (www.nrcan.gc.ca/node/9309)
[6] *Fundamentals of Remote Sensing and Airphoto Interpretation*, Avery T. E and Berlin, G.L.: Jenson Books Inc., (Jenson Online)
[7] *National Wetland Atlas: Maharashtra, SAC/RESA/AFEG/NWIA/ATLAS/19/2009, Space Applications Centre (ISRO), Technical Report, Ahmedabad, India, 2009*
[8] Website (http://speclab.cr.usgs.gov/spectral-lib.html)
[9] Website (http://speclib.jpl.nasa.gov/)
[10] Christensen P. R., Bandfield J. L., Hamilton V. E., Howard D. A., Lane M. D. and Piatek J. L.: A thermal emission spectral library of rock-forming minerals, *J. Geophysical Research (Planets), 105, 9735 (2000)*
[11] Clark B. E., Fanale F. P., and Salisbury J. W.: Meteorite-Asteroid Spectral Comparison, the Effects of Combination, Melting, and Recrystallization: *Icarus, 97, 288-297 (1992)*
[12] Ducart D. F., Crosta A. P., Souza C. R. and Coniclio J.: Alteration Mineralogy At The Cerro La Mina Epithermal Prospect, Patagonia, Argentina: Field Mapping, Shortwave Infrared Spectroscopy, and ASTER Images, *Economic Geology, 101, 981−996 (2006)*
[13] Hellman M. J. and Ramsey M. S. : Analysis Of Hot Springs And Associated Deposits in Yellowstone National Park using ASTER and AVIRIS Remote Sensing, *J. Volcanology and Geothermal Research, 135, 195−219 (2004)*
[14] Hubbard B. E. and Crowley J. K.: Mineral Mapping On The Chilean-Bolivian Altiplano Using Co-Orbital ALI, ASTER and Hyperion Imagery: Data Dimensionality Issues and Solutions, *Rem. Sens. Environ., 99, 173−186 (2005)*
[15] Rockwell B. W. and Hofstra A. H. : Identification Of Quartz And Carbonate Minerals Across Northern Nevada Using ASTER Thermal Infrared Emissivity Data - Implications for Geologic Mapping and Mineral Resource Investigations in Well-Studied and Frontier Areas, *Geosphere, 4, 218−246 (2008)*
[16] Rowan L. C., Hook S. J., Abrams M. J., & Mars J. C.: A New Satellite Imaging System for Mapping Hydrothermally Altered Rocks: An Example from the Cuprite, Nevada Mining District USA, *Economic Geology Bulletin, 98, 1019−1027 (2003)*
[17] Vaughan R. G., Hook S. J., Calvin W. M., & Taranik J. V.: Surface Mineral Mapping at Steamboat Springs, Nevada, USA, with Multi-Wavelength Thermal Infrared Images, *Rem. Sens. Environ., 99, 140−158 (2005)*
[18] Vaughan R. G., Kervyn M., Realmuto V. J., Abrams M. J., and Hook S. J.: Satellite Thermal Infrared Measurements of Recent Volcanic Activity at Oldoinyo Lengai, Tanzania, *J. Volcanolgy and Geothermal Research, 173, 196−206 (2008)*
[19] Zhang X., Pamer M., & Duke N.: Lithologic and Mineral Information Extraction for Gold Exploration Using ASTER Data in the South Chocolate Mountains (California), *ISPRS J. Photogrammetry and Rem. Sens., 62, 271−282 (2007)*
[20] ERDAS IMAGINE Field Guide (online)
[21] *Pattern Classification*, Duda R.O., Hart P.E., Strok D.G.: 2nd edition, e-book (online)
[22] *Pattern Recognition Principles*, Tou, J..T and Gonzalves, R.C.: Addison-Wesley, 1974
[23] Wong T. H., Mansor S. B., Mispan M. R, Ahmad N. and Sulaiman W.N.A.: Feature Extraction Based on Object Oriented Analysis, *Website (http://www.ecognition.com/sites/default/files/370_wongtaihong.pdf)*
[24] Baatz M.A.S.: Object-Oriented and Multi-Scale Image Analysis in Semantic Networks *Proceed. Of the 2nd Int. Symp. On Operationalization of Rem. Sens., (ITC) (1999)*
[25] Mitri G. H. and Gitas I. Z. : The Development of an Object-Oriented Classification Model for Operational Burned Area Mapping on the Mediterranean Island of Thasos using LANDSAT TM Images, *Forest Fire Research & Wildland Fire Safety, Viegas (Ed.) Millpress, Rotterdam, (2002)*
[26] Hoffman T., PuzichaJ. And Jordan M. I.: Unsupervised Texture Segmentation in a deterministic Annealing Framework, *IEEE Trans. Pattern Analysis and Machine Intelligence, 20 (8), 803-818 (1998)*

Author Profile

Tutu Sengupta, Doctorate in Physics, RTM Nagpur University. Presently serving as Associate Scientist, Maharashtra Remote Sensing Application Centre, Autonomous Body, Dept. of Planning, Govt. of Maharashtra. Designated as Guardian Scientist, Water Resources, Geo-spatial Services, Maharashtra. Principal Investigator (PI) in several Central and State water related projects.

Shagun Sengupta, did B.E in Information Technology from Savitribai Phule Pune University. She is a IIE WeTech Goldman Sachs Scholar (2017-18). Did project on ‘Electronic Voting System using Blockchain’, patent pending. Currently working as Software Development Engineer with keen interest in Machine Learning, Data Analytics and Data Science and how these can be used for Environmental Impact Assessment and Sustainable Development.

Satish J Sharma, Doctorate in Physics, RTM Nagpur University. Serving as Professor and Head of Department of Electronics and Computer Science, RTM Nagpur University. Field of specialization includes Acoustics, instrumentation in ultrasonics, virtual instrumentation, embedded systems, artificial neural network, nano science and nano technology.