Microwave Remote Sensing Scope and Challenges in Image Interpretation – A Review

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DOI: 10.54882/13202313202317467

Abstract: It is a known fact that there are three powerful sensing techniques to observe the activities on the earth surface. They are given as optical remote sensing, thermal remote sensing, and microwave remote sensing. There are some practical and theoretical differences between the sensors and their applications. The aim of the present review is to show how the microwave sensing is different from other sensing techniques by describing the properties of all the types of remote sensors and how these properties will benefit the scientists and researchers for going into the microwave remote sensing. This work also focusses the major applications of all the sensors and discusses the scope of various mechanisms like interferometry, polarization and issues in microwave remote sensing in the context of image interpretation.

Keywords: Microwave, Optical, Infrared, Spatial resolution, Radiometric resolution, Electromagnetic radiation, Geometric correction.

I. Introduction

Sensors are sophisticated devices that are more often in use to give response to some type of input from the physical environment. In a prescribed way, sensors are used to give the sensible difference between the elements of earth surface. The input to the sensor can come from any type of resource elements like light, heat, moisture water, motion etc. Remote sensors are typical devices that takes the energy from the earth surface in the form of signals and convert them into human readable form in the form of images. According to the Cambridge English Dictionary, the word “remote” means far away in distance and “sensing” means being aware of something. Thus, “remote sensing” can be literally defined as being aware of something from a far distance. The first work of remote sensing was taking pictures from the balloons using the newly invented camera in 1840. Ms. Evelyn Pruitt of United States working in Naval research was the first person to use the term "remote sensing", which is now commonly used to describe the science and art of identifying, observing, and measuring an object without coming into direct contact with it.

II. Optical Remote Sensing

Optical Remote Sensing in the electromagnetic spectrum uses visible, near infrared (NIR) and short-wave infrared (SWIR) sensors to collect the information of the earth's surface in the form of imagery by detecting the solar radiation reflected from targets on the ground. Optical sensors are restricted to coverage of the optical region generally considered to extend from 0.4 to 1000 μm, but restricted further by atmospheric

transmission to windows within the 0.4- to 15-pm region, and emphasizes modern sensors and technology development as well as future sensors and missions. Optical remote sensing signals are divided into channels or bands. Instead of frequencies, wavelengths are commonly used to distinguish Optical remote sensing bands. Human eyes are sensitive to the band of wavelengths from about 0.4 to about 0.7 μm, which is called visible band in optical remote sensing. The visible band consists of three colors: red, green, and blue (RGB). Blue wavelengths are approximately 0.4–0.5 μm, green is 0.5–0.6 μm, and red is 0.6–0.7 μm. The three visible-light bands can be combined into a single band called panchromatic band or separately into blue, green, and red bands, respectively. Electromagnetic radiation with wavelengths between 0.7 and 1.3 μm is the near infrared (NIR) band; EMR with wavelengths between 1.3 and 3.0 μm is the shortwave infrared (SWIR) band. Since the NIR and SWIR bands are strongly reflected from the Earth’s surface, they both are together called the reflected infrared band. Optical remote sensing systems are classified into the four types as (1) Panchromatic Imaging System (2) Multispectral Imaging System (3) Super spectral Imaging System and (4) Hyperspectral Imaging System.

A. Applications of Optical Remote Sensing

Optical remote sensing can be directly used for detecting things on the earth related to their position, if they have changed, and so on. In fact, indirect applications of optical remote sensing are even broader and deeper, and are playing an active role in sustainable development all over the world. Optical remote sensing is an effective and efficient technique for many land-use- and land-cover-related investigations at scales from landscape to global. The greater the spatial scales, the more advantages optical remote sensing can have. As a conventional and oldest remote sensing technique, optical remote sensing has been broadly used since the end of World War II. Airborne and space borne optical remote sensing has made unique contributions to understanding the dynamics of the atmosphere, oceans, and the vegetation cover of the land and has provided new perspectives in the study of the solid Earth. Associated with continuous advances in remote sensing, optical remote sensing has been applied in many fields, including archaeology, aquatic ecosystems, biodiversity, climatology, forest measurements, global change, habitat detection and conservation, human health, invasive species, land use and land cover, urban morphology, vegetation stress, and wildfire management. The applications of optical remote sensing is explained in all the possible areas with the methodology used along with the sensor type in Table 1.

Table- I: Applications of optical remote sensing

Application	Sub-category	Methodology	Satellite
Object detection	Aircraft detection	Fully Convolution Neural Networks [1], Rotation-invariant hough forest [2]	Quickbird [1, 2]
	Ship detection	Visual saliency and Adaboost Classifier [3], Saliency and rotation invariant descriptor [4]	Quickbird [3, 4]
	Vehicle detection	"Reed-Xiaoli" (RX) algorithm + Adaboost algorithm+Haar like features [5], Random forest+CNN [6]	Google Earth [5] LIDAR [6]
	Oil tank detection	Ellipse Line Segment Detector + HOG [7] Visual saliency + Hough transform [8]	Quickbird [7, 8]
	Cloud detection	Color model and threshold based image segmentation [9], Cloud Index and Cloud shadow Index [10]	WorldView-2, XY-3, Pleiades-1, GF-1 [9], IKONOS [10]
Urban Planning and development	Building detection	Morphological operations+λ scheduling algorithm [11]	LiDAR [11]
	Road detection	Image segmentation using Deep Convolution neural networks [12], Gaussian Mixture Model [13]	GF-2 satellite [12] WorldView-2 [13]
	LULC mapping	Texture feature analysis + Random Forest Classifier [14]	LiDAR [14]
Agriculture	Crop mapping	NDVI Statistics [15], Vegetation Indices [16]	SPOT [15], Landsat [16]
	Crop Yield estimation	Vegetation Statistics [17], Leaf Area Index (LAI) and Average Canopy Height (Hcanopy) [18]	AVHRR, MODIS and SPOT [17], GF-1 [18]
Hydrology	Snow cover mapping	Vegetation indices [19], Snow cover index [20]	PROBA-V [19] Landsat [20]
	Surface water monitoring	Normalized Difference water Index [21] Modified optimized water index [22]	Landsat 8 [21, 22]
Forestry	Forest Mapping	Region growing segmentation [23] Physical parameters [24]	LiDAR [23, 24]
Ocean monitoring	Ocean current estimation	Maximum cross correlation [25]	Geostationary Ocean Color Imager [25]
	Surface temperature estimation	Suspended particulate matter (SPM) concentration on the value of sea surface emissivity (SSE) [26]	MODIS [26]
Disaster Management	Volcano Monitoring	Physical properties and aerial survey [27] Back propagation neural network [28]	LiDAR DTM [27] AVHRR [28]
	Oil spill detection	Recursive Neural network [29], Image segmentation with saliency map model (Tamminga et al. 2015)	Landsat and DubaiSat-2 [29], Landsat 8, GF-1[30]

III. THERMAL INFRARED REMOTE SENSING

Thermal remote sensing is based on the measurement of electromagnetic radiation in the infrared region of the spectrum. The astronomer Sir Frederick William Herschel discovered the infrared portion of the electromagnetic spectrum in 1800. The data collected by the Television IR Operational Satellite (TIROS) launched in 1960 is the first published satellite of the thermal remote sensing by the U. S. Later the thermal infrared data of coarse resolution were ideal for monitoring regional cloud patterns and frontal movement.

Thermal infrared has a wavelength of between 8.0 to 15 µm. Thermal energies are easily absorbed by water and other gases due to its wavelength restrictions and so the thermal images are recorded in two particular wavelengths of 3 to 5 µm and 8 to 15 µm. Hence, thermal IR imagery is difficult to interpret and process because there is absorption by moisture in the atmosphere. The objects, which has a temperature greater than zero emits the thermal radiation. Thermal energies cannot be absorbed by visualization, since the eyes of human beings are sensitive to shorter wavelengths. Normally thermal energy can be felt with the help of a touch. Thermal imagery can be acquired during the day or night, as it is dependent on the temperature of the objects but not on the sunlight. There are some key factors such as thermal conductivity, thermal capacity and thermal inertia on which the results of thermal imagery depends. Thermal energies can be absorbed even in complete darkness, but cannot penetrate through the clouds because of wavelength. However, thermal energy can be absorbed in smoke.

A. Applications of Thermal Infrared Remote Sensing

Optical remote sensing can be directly used for detecting things on the earth related to their position, if they have changed, and so on. In fact, indirect applications of optical remote sensing are even broader and deeper, and are playing an active role in sustainable development all over the world. Several centimetres of the material's surface can be represented by the thermal property. The unique property of thermal remote sensing helps in extracting information from the emitted radiations of soil moisture, rock types, minerals and geothermal anomalies. The concept of thermal remote sensing is quite complementary to other remote sensing data. Thermal remote sensing has the ability to observe temperature variations from the emitted infrared radiation of the targets and this phenomenon made the users to understand the significant changes the environment undergoes. There are some intensive applications of thermal remote sensing. Initially, thermal remote sensing was developed for military purposes; later thermal imaging has been developed for fire and rescue teams in forests, law enforcement, maintenance operations, security professionals, and more. The application of thermal remote sensing is extended to detect approaching people or vehicles, to track the footsteps of a fugitive, or to learn why a fire resists extinguishment. The applications of thermal remote sensing are given in Table 2. The most important applications of thermal remote sensing are temperature estimation of the earth's surface, crop mapping and monitoring.

Table- II: Applications of thermal remote sensing

Application	Sub-category	Methodology	Satellite
Object detection	Ship detection	Chess board segmentation [31] Region based deep forest using convolution neural networks [32]	MACS - Maritime Security (Mar) [31] TG-1 satellite [32]
	Cloud detection	Cloud kappa values [33] Cloud detection algorithm [34]	MODIS [33, 34]
	Oil tank detection	LBP features, EOH features and invariant moment features [35]	TIR [35]
Urban Planning and development	Soil Moisture	Normalized Difference Vegetation Index + temperature difference [36], Mixture pixel reflectance [37]	MODIS [36] IKONOS, and NOAA [37]
	Temperature estimation	Multi-temporal air temperature estimation scheme [38]	MODIS [38]
Agriculture	Crop damage assessment	Fractional green cover, leaf area index, and above ground biomass (AGB) [39]	MODIS [39]
	Drought stress Monitoring	Component object model [40] Visible and shortwave infrared drought index [41]	MODIS [40, 41]
	Evapotranspiration	Vegetation health index and standardized precipitation index [42], Crop water stress index [43]	GOES [42] Landsat index [43]
	Soil moisture	Vegetation indices and Artificial neural networks [44], Soil moisture and Vegetation indices [45]	AggieAir [44] Landsat [45]
Hydrology	Temperature estimation	Pixel water-fraction maps are then input to a gradient descent algorithm [46]	MODIS, ASTER [46]
Forestry	Forest mapping	Thermal Integrated Vegetation Index (TLIVI) and Advanced Thermal Integrated Vegetation Index (ATLIVI) [47]	Landsat ETM [47]
	Forest fire detection	Stochastic fire model + biband threshold method [48] Agent based algorithm [49]	MODIS [48, 49]
Ocean and sea monitoring	Ocean current estimation	Maximum cross co-relation [50]	MODIS [50]

	Surface temperature estimation	Empirical parameters [51]	AVHRR [51]
Disaster Management	Volcano monitoring	Curve-fitting algorithm [52], Absorbing aerosol index + PCA [53]	Hyperspectral TIR imager algorithm [52], MODIS [53]
	Fire accidents	Spectral and spatial pixel features [54]	VIRR [54]
	Oil spill detection	Planks constant and physical properties [55]	Landat-7 ETM+ and Landsat-5 TM [55]
	Flood monitoring	Change detection analyses [56], Robust satellite technique [57]	ASTER, ETM+ [56], MODIS [57]

IV. MICROWAVE REMOTE SENSING

Microwave remote sensing fits in both active and passive forms of remote sensing The wavelength of microwave portion of the spectrum ranges from 1 cm to 1 m approximately. The wavelength attribute adds more advantages to the microwave remote sensing and has special application oriented characteristics compared to the visible and infrared remote sensing. Longer wavelengths of microwave radiation helps in penetrating through smoke, cloud cover, haze, dust and made the users feel comfortable to gather the information of targets under almost all weather conditions. The property of passive microwave sensing is similar to that of visible and thermal remote sensing. Microwave energy emitted from the objects will be of less magnitude and the passive microwave remote sensor within the field of view detects it. In addition to the temperature, the passive microwave remote sensor collects moisture properties of the emitted object or surface. An additional heavy equipment antenna is used in radiometers and scanners of passive sensors to detect and record the microwave energy. Whereas in active microwave sensing own source of microwave radiation is provided to illuminate the target. Imaging and Non-Imaging are two categories of active microwave remote sensing. RADAR is the active form of microwave remote sensors for imaging purposes. RADAR stands for RAdio Detection And Ranging, which fundamentally characterises the function and operation of a radar sensor. The imaging by radar is named as synthetic aperture radar (SAR) imaging. The active microwave remote sensor transmits a radar signal towards the target and detects the backscattered portion of the signal. The strength of the backscattered signal is measured to discriminate between different targets, and the time delay between the transmitted and reflected signals determines the distance (or range) to the target. The major advantage of active microwave remote sensing is the capability of the radiation to penetrate through cloud cover, so it can be applied at most weather conditions. The radar is an active form of microwave remote sensing used to image the surface at any time, day or night. These are the two primary advantages of radar: all-weather and day or night imaging.

A. Application of Microwave Remote Sensing

Passive microwave remote sensing has the same principles of thermal remote sensing. The energies in microwave remote sensing are quite low when compared to the temperature of the objects in thermal remote sensing. Hence, the large area should be covered for collecting the information. In 1978, the application of passive microwave remote sensing began with the Electrically Scanning Microwave Radiometer (ESMR). The main areas of applications for passive microwave remote sensing are sea ice detection, ocean monitoring, soil moisture estimation etc. Active microwave remote sensing has an important property of high resolution irrespective of flight altitude, and weather conditions. Active form of microwave remote sensing is radar remote sensing. Development of SAR imaging happened in 1950s for better resolution than fixed radar and applied in defence applications covering large area. The important applications of radar are in the areas of glaciology, topography, geology, oceanography and forestry. Radar imaging is mainly useful for disaster management applications of volcano and earthquake monitoring as a part of differential interferometry. It is also useful in environment monitoring like urban growth, land use land cover monitoring, oil spills detection, flooding, global change and military surveillance. SAR can also be implemented as inverse SAR by observing a moving target over a substantial time with a stationary antenna.

Table- III: Applications of microwave remote sensing

Application	Sub-category	Methodology	Satellite
Object detection	Aircraft detection	Image segmentation with saliency map [58] Threshold based image segmentation [59]	Terrasar-X [58, 59]
	Ship detection	Image Uniformity Description Factor [60] Boundary box + Feature maps [61]	UAVSAR [60] Sentinel-1 [61]
Urban Planning	Building detection	Morphological operations and image segmentation [62], Deep neural network and convolution neural network [63]	TerraSAR-X [62, 63]

	Road extraction	Region growing image segmentation [64], Fuzzy algorithm [65]	TerraSAR-X [64, 65]
	Land use land cover	Object based approach [66] Deep belief networks [67]	PALSAR [66] RADARSAT-2 [67]
Agriculture	Crop mapping	Object based features [68], Texture features along with SVM and KNN [69]	TerraSAR-X [68, 69]
	Soil moisture	Physical properties and NDVI along with ANN [70], Image ratioing and principle component analysis [71]	Sentinel 1 [70] RADARSAT 1 [71]
Hydrology	Snow cover and mapping	Coherence analysis [72], Satellite retrieval algorithm [73]	ENVISAT [72] AMSR-E and AMSR2 [73]
Forestry	Forest Mapping	Object based classification [74], Texture features along with random forest classifier [75]	ENVISAT [74] ALOS-2, TerraSAR-X [75]
Ocean and sea management	Iceberg detection	Physical properties and threshold methodology [76], Object based image segmentation [77]	RADARSAT-2 [76] ENVISAT ASAR [77]
	Wind speed detection	Heapsort bucket method with Gauss–Markov theorem [78], Physical and mathematical properties [79]	RADARSAT 2 [78] PALSAR [79]
Disaster Management	Landslide Monitoring	NDVI threshold [80], Backscattering coefficient difference and intensity correlation [81]	RADARSAT-2 [80] COSMO-SkyMed [81]
	Oil spill detection	Genetic algorithm [82], Artificial Neural Networks [83]	RADARSAT-2 [82], ERS-2 SAR and ENVSAT ASAR [83]
	Flood Monitoring	Change detection using wavelet analysis [84] Neuro-fuzzy flood mapping technique [85]	TerraSAR-X [84] COSMO-SkyMed [85]

V. CHALLENGES IN REMOTE SENSING

The challenges in the remote sensing techniques to be resolved under different aspects like the sensor capabilities, resolution techniques, image interpretation and analysis are given in Table 4.

VI. IMAGE INTERPRETATION

Interpretation of the image is the most extensive form to perform remote sensing analysis through the detection and extraction of features in the target image. Image interpretation is the procedure to identify the pixel values of the image with some analytical power. Image interpretation is also given as extracting the qualitative and quantitative information including various attributes like shape, structure, object detection, function, condition, quality, etc. with the help of human computer interaction. The method of image interpretation is highly robust technique in identifying different features of vegetation type and condition, anthropogenic landscape features of industries, roads and geographical structures. The very good need of successful image interpretation is a good technical analyst with some familiarity about the image processing techniques. There are four ways in which remote sensing differs from our real life: (1) On the air process is responsible for the Imagery collection (2) Many sensors record imagery beyond the visible portion of the electromagnetic spectrum. A colour infrared image of healthy vegetation will appear red rather than green. (3) Imagery may be acquired at unfamiliar resolutions and scales. (4) Depth is lost, while viewing a two-dimensional image, unless one can view it stereoscopically so as to simulate the third dimension of height.

Table- IV: Challenges of remote sensing techniques

Application	Sensor	Challenges
Agriculture	Optical	Cloud cover is an important obstacle for optical satellite data. It makes use of time series much more complicated. Spectral signatures overlap in the optical remote sensing imagery makes the user difficult to separate irrigated fields from non-irrigated plots in humid areas.
	Thermal	Thermal behaviours of crops vary with climatic conditions. Less accurate for coarse resolution and less reliable for the classes with contrast emissivities
	Microwave	The coarse resolution of space borne instrument interpretations remains a challenge. The adoption of SAR imagery in agriculture monitoring is a major challenge due to scattering.
Forestry	Optical	Cloud cover is considered as a serious limitation in tropical regions. Optical images records spectral responses due the interaction between the solar radiance and forest stand canopies. The spectral response serves as a limitation in the ability to predict forest biomass through optical remote sensing imagery.
	Thermal	Approximate atmospheric corrections are required. MIR and TIR requires channel measurements acquired during day and night time of atmospheric windows. Geometry registration of thermal data is required at different angles increasing the additional complexity to the user.
	Microwave	A common challenge is to quantify spatial and temporal patterns of forest cover. Water stress in forest areas influences a lot due to dielectric properties and geometric changes and it remains a challenge to separate the artefacts of scatterometer for pre-processing of data. The main problem of Interferometry SAR at X-band is that the interferometric rationality is not very high over the surfaces of heavy vegetation cover and forests.
Hydrology	Optical	The reflectance of radiation caused due variance in water column depth and optical properties of water causes system to be environmentally limited.

	Thermal	Thermal sensors becomes heat as it collects the information from the target as a radiation. The coarse spatial resolution of thermal data poses additional problems in geometrically registering it to other data, especially when the latter have much higher spatial resolution.
Ocean monitoring	Optical	Across-image variation occurs due to the environmental components such as water inherent optical properties, sun elevation, bathymetry, wind speed and sensor noise characteristics.
	Thermal	The ambiguity of atmospheric summaries may have strong effects on the accuracy of land surface temperature (LST) retrieval. As most of the sea area is covered by clouds, the thermal data needs atmospheric corrections.
	Microwave	The discrimination between open water and sea ice becomes difficult due to variable backscattering of open water due to wind conditions for the co-polarized (HH or VV) data at C-band.
Geology and mining	Optical	There is no ground truth in meteorological applications for optical data due to small sample size, as a result geoscience applications face spatio-temporal structure challenges showing non-stationary characteristics and follows non-linear relationships.
	Thermal	As discussed earlier accurate geometric registration is required in atmospheric windows of MIR and TIR channels. As a result initial guess values are required to predict the atmospheric profiles.
	Microwave	Data interpretation of the wide range of materials with different backscattered radiation of different wavelengths is thus rendered nearly impossible, resulting in spatial resolutions as large as 20 to 100 km.
Disaster Management	Optical	Short length of record is the major limitations of the currently available satellite observations. A large size data is needed to analyse the data of gravity recovery and climate experiment, which is unavailable. Temporal and spatial dynamics of post-fire change detection estimation became a big challenge especially in evaluating the post-fire boreal forest characteristic.
	Thermal	Various factors like horizontal advection, variation of atmospheric variables like wind speed, vapour pressure deficit are not incorporated, which varies the target information a lot.
	Microwave	To predict the possible developments in the entire flood area with accurate extent is another major challenge. Another misclassification of oil spilt dark areas in oil spill detection with look-alikes such as rain cells, calm sea surfaces and biogenic slicks is a major challenge.
Urban planning and development	Optical	In multi-temporal analysis, especially in change detection, it is difficult to co-relate the features of isolated pixels to the objects. There are additional challenges like large variations in the visual appearance of objects caused by viewpoint variation, occlusion, background clutter, illumination, shadow.
	Thermal	The major limitation of thermal remote sensing is that high spatial resolution sensors have low temporal resolution and vice versa. The data of high spatial resolution sensors are often associated with a number of challenges that include high acquisition costs, small swath width and low temporal resolution, which limit their value for change detection analysis studies, especially over large areas.
	Microwave	Speckle noise is the major challenge and also the noise leads to misclassification in detection of objects.

A. Optical Remote Sensing Image Interpretation

Image interpretation in optical remote sensing data contains different types of important information like radiometric resolution indicating the brightness, intensity, tone, spectral Information with colour and hue information, textural Information, geometric and contextual Information. In optical wavelength, the transmission in clear water is generally high. The blue end of the spectrum has the maximum reflectance and decreases as wavelength increases. Hence, clear water appears dark-bluish. Muddled water has some deposit suspension that increases the reflectance in the red end of the spectrum, accounting for its brownish appearance. The reflectance of bare soil generally depends on its composition. Hence, the soil appears yellowish-red to the eye. Vegetation occupies a special place in the optical image due to the spectral nature and distinguishes from other land cover types. The absorption of radiation by chlorophyll for the process of photosynthesis gives the less reflectance in blue and red regions of the spectrum. The reflectance is peak at the green region leading to the green colour of vegetation. Hence, vegetation is identified in the higher region of near infrared spectrum. The shape of the reflectance spectrum can be used for identification of vegetation type. Strong absorption bands for water are around 1.45, 1.95 and 2.50 µm, but outside these absorption bands in the short infrared region, reflectance of leaves generally increases when leaf liquid water content decreases and this property is used for identifying tree types and plant conditions from remote sensing images. The short infrared band can be used in detecting plant drought stress and delineating burnt areas and fire-affected vegetation. The SWIR band is also sensitive to the thermal radiation emitted by intense fires, and hence can be used to detect active fires, especially during night-time when the background interference from SWIR in reflected sunlight is absent.

B. Thermal Remote Sensing Image Interpretation

Mostly thermal images are acquired in single band giving the output data as greyscale images. Darker areas of thermal images are cooler in nature, whereas brighter areas indicate areas that are warmer. To differentiate temperature in the single band thermal images, pseudo-color thermal images needs to be displayed. The information obtained from thermal images are obtained from reflected radiation. Remote sensing of direct temperature effects is carried out by sensing radiation emitted from matter in the thermal infrared region of the spectrum. The amount of solar radiation reflected from land and sea surfaces, as well as the amount absorbed, depends partly on that portion of energy from the sun that reaches these surfaces. A thermal sensor detects radiant energy from a surface target, heated through radiation (solar insolation and sky radiance), convention (atmospheric circulation) and conduction (through the ground). A primary objective of temperature measurements and related thermal responses is to infer something about the nature of the composition and other physical attributes of materials at the earth's surface and, in its atmosphere. Interpreting thermal data and images of temperature distribution over an area is complex.

C. Microwave Remote Sensing Image Interpretation

Radar images are active form images for microwave remote sensing have certain characteristics that are fundamentally different from images obtained by using optical sensors and thermal remote sensors. These unique characteristics are the significance of the imaging radar technique, and are related to speckle, texture or geometry. During SAR image analysis, the technician must keep in mind the fact that, even if the information is presented as an analog product on photographic paper, the radar visualizes the scene in a very different way from the human eye or from an optical sensor. The backscattered energy from the target scenes are represented as grey levels. Shadows in radar image are due to the oblique incidence angle of microwave radiation emitted by the radar system and not to geometry of solar illumination. The intensity of the backscattered signal varies according to roughness, dielectric properties and local slope. Thus, the radar signal refers mainly to geometrical properties of the target. In contrast, measurements in the visible/infrared region use optical sensors where target response is related to colours, chemical composition and temperature.

VII. CONCLUSION

In this paper, the various platforms and orbits are considered along with their advantages and disadvantages. The mostly used applications of optical, thermal and microwave remote sensing was listed. And also the challenges of the remote sensing techniques were illustrated for various types of applications. The challenges are focussed not only on the image processing, but also on the hardware issues. Image interpretation keys are given for the sensors which motivates the young researches and scientists to go for the work on various domains of remote sensing. Images acquired by microwave remote sensing has some basic disadvantages like most of the tools used by various specialists did not work properly with them and it should suffice to say that a SAR image models are formed by sending a microwave signal towards the target and by recording and processing the reflected echo. The illumination used is coherent, and it can be proved that when this technique is used a special kind of speckle noise appears. It is convenient to recall that these images are formed using electromagnetic signals, complex by nature. In spite of the above discussed disadvantages, SAR images are considered one of the greatest technological leaps in remote sensing.

There are various types of properties and observations which makes the microwave remote sensing unique and different from optical and thermal remote sensing. Some virtues of these kind of techniques are briefly summarized below:

1) *Polarimetry:* Polarization techniques afford a prosperity of qualitative and quantitative information about various assets of a surface. The polarization concept can help to determine which polarization (H, V, HH, VV, HV, VH) images may improve the signal from a particular feature of land area, forest mapping and rock surfaces. Thus Polarimetry data is formed in different channels forming the full scattered matrix used to observe dielectric properties of surfaces, target orientation etc.
2) *Interferometry:* The various challenges in microwave remote sensing can be addressed by developing good quality digital elevation models using InSAR technique.
3) *ScanSAR:* At this mode, the surface area covered will be triple to the normal beam mode with the same cost. The best examples of satellites are RADARSAT-1, RADARSAT-2 and ASAR.
4) *SLAR:* It is given as Side Looking Airborne Radar, an active radar to acquire the information from aircraft by looking in a side angle. The SLAR project generally takes 1:250,000-scale topographic maps and the detail of the image strips will be photograph-like. These are mainly used to cover the cloud covered areas.
5) *Bandwidth:* The bandwidth of microwaves is larger leading to more information transmission and point-to-point communications.
6) *Fading:* Line of sight propagation technique minimizes the fading effect for the wavelengths of microwave region, whereas fading of the signal occurs for optical and thermal remote sensors.
7) *Image Interpretation:* The various drawbacks of optical and thermal image interpretation especially multiresolution analysis, spatial and spectral resolution mismatch analysis, and geometric corrections. The geometric corrections in microwave remote sensing can overcome terrain correction.

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