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REVIEW PAPER

Remote Sensing in Strategic Applications

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ABSTRACT

Remote sensing has come a long way in the last three decades. The technology has reached all spheres of human activity and affected our life in innumerable ways. Some of the recent studies in this area have contributed towards better resolution, better precision and opened up a host of new application areas. The era of hyperspectral imaging is on, and it is expected that it will soon overtake the multispectral imaging within a few years. Synthetic aperture radar interferometery has taken strides towards providing accurate digital elevation models than ever before, the recent shuttle radar topography mission has proven its capability, with a near coverage of the whole globe and the dictum of digital earth is soon going to be a reality. Information extraction from remote sensing images has reached new heights with recent methodologies like the neural networks and contextual classification, enabling to create and incorporate external knowledge into the classification process. Some of these emerging technologies and processing methods in the context of strategic application areas have been discussed.

Keywords: Hyperspectral imaging, radar interferometry, fractal characterisation, isarithm, variogram, triangular prism, neural networks, remote sensing, single-pass interferometry

1. INTRODUCTION

Extended reconnaissance i.e. the ability to supply responsive and sustained intelligence data from anywhere within any territory, day or night, regardless of weather, is one of the important components of the defence programmes in any country. The nature of future conflict will not be location-dependant, but will manifest itself in near-simultaneous regional conflicts requiring rapid deployment and action under a broad variety of environmental and political conditions. Some of the important requirements to achieve this are: (i) Hundreds of point targets per day, (ii) thousands of square kilometers coverage per day, (iii) mapping, charting and geodesy of thousands of square kilometers per day, and (iv) total imagery coverage of tens of thousands of square kilometers per day.

The sensors, platforms, and information components of the architecture have to be modular and flexible to facilitate fast, efficient configuration and deployment across a range of contingencies. Issues relating to the diverse data, resolution selection and processing methods are important in this context. Imaging spectrometry and synthetic aperture radar (SAR) interferometry are some of the technologies emerging in this direction. New processing methods like neural networks, contextual classification and fractal characterisation have revolutionised the way one looks at the information and also the amount and quality of data that can be extracted.

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2. SCALE-DEPENDENT ANALYSIS

Maps and other models of physical phenomena are simplified abstractions of reality and necessarily involve some degree of generalisation. When performed correctly, generalisation reduces both the volume of data that must be stored and analysed, and clarifies the analyses itself by separating a signal from noise. For geographical analysis, a key concept in the generalisation process is scale. Some of the measures of scale are:

- **Cartographic Scale:** The proportion of distance on a map to the corresponding distance on the ground.
- **Geographic (observational) Scale:** The size or spatial extent of the study.
- **Operational Scale:** The spatial domain over which certain processes operate in the environment.
- **Measurement Scale:** The smallest distinguishable object or parts of an object.

Landscape processes are generally hierarchical in pattern and structure, and a study of the relations between the patterns at different levels in this hierarchy can provide a better understanding of the scale and resolution problem. Thus, an analyst must first understand the research question and the spatial domain of the process being measured (including the spatial organisation of the features of interest) to determine the extent of the required input data and the cartographic scale of the output maps. The research question and the supporting inputs and outputs necessary to address the question, together with the availability of data and the capabilities of the analyst (knowledge, hardware, and software), then determines what resolution is needed in the input data.

2.1 Integration of Expert Knowledge in Image Classification Procedures

One of the methods of integrating expert knowledge is using image segmentation based on the Bayesian probability theory[1], which expresses a relationship between conditional and unconditional probabilities. The observed remote sensing data, the radiometric and model parameters are related by the Bayesian theory. The goal is to estimate the maximum probability values for the model parameters from remote sensing data given GIS. This method integrates the information knowledge about objects, processes stored in GIS and other contextual information[2]. In the target identification process for military applications, this method provides means to incorporate the existing knowledge about the area, which serves as a starting point in the analysis. An airstrip may be identified based on the surrounding buildings or other features that are already known, and this historical contextual knowledge can be used to identify it.

A radiometric likelihood generator calculates the probability of the radiometry given the radiometric class (from GIS derived from existing knowledge) and stores the likelihood vectors in radiometric evidence maps. The geometric hypothesis generator is mainly for the image partitioning of the GIS data with certain geometric constraints (e.g. neighbourhood constraint hypothesis), the output of this operation is the generation of the hypothesis map, which is derived from the knowledge hidden in GIS. Morphological parameters like erosion (expansion of a geometry given some constraints by a structuring element; the structuring element is the same as the mask or kernel in spatial filtering) and dilation (contraction of a geometry given a set of constraints by a structuring element).

In the classical maximum likelihood per-pixel algorithm, the class to which the pixel is finally assigned is that with the highest probability. Probabilities of class membership on which the assignment is based, are not available after the assignment. Contextual classification method requires the class membership of the probabilities of each class, (e.g. agriculture 0.10 and forest 0.90), therefore the class membership probabilities or the radiometric likelihood vectors are generated on the Bayesian estimation providing a link between the radiometric parameters of object classes and the data is used to estimate the statistical parameters like the mean vector and covariance matrix. The result of this process is the generation of the likelihood map (or evidence map) for the area. Likelihood vectors are stored in these maps and they reflect the probabilities that a sample belongs to each of the defined set of possible landcover classes, obtained by the supervised classification of the multi-band satellite images. For each radiometric class a likelihood map is generated (Fig. 1).

The geometric hypothesis generator takes care of the available data and/or knowledge contained in the GIS database about the shape of the object (e.g. airstrip, tankers, etc.) and processes can be used to predict the remote sensing data about the presence of the target by shape hypothesis generation. The hypothesis generation begins with the assumption that a target is surrounded by certain known objects. The morphological operation is aided by the assumptions like; certain types of structures exist and either the target is detected by shrinking or expanding these features. Several such premises can be incorporated in the knowledge domain to facilitate the morphological operations.

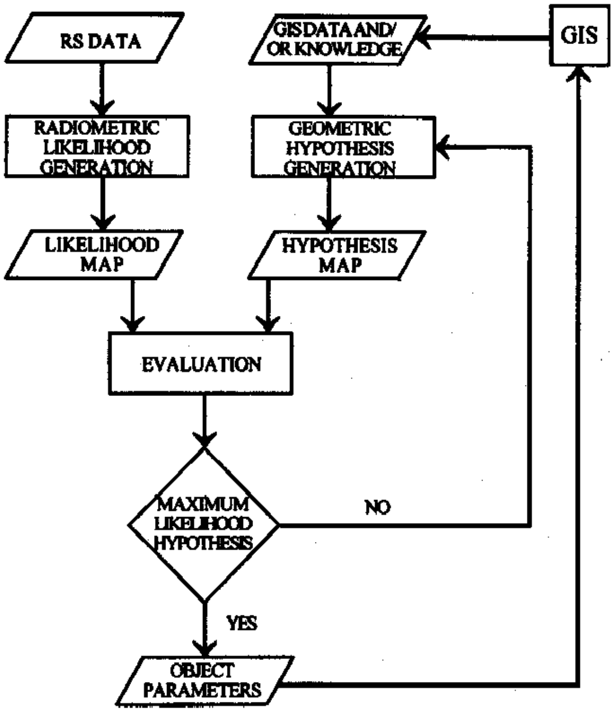

Figure 1. Conceptual representation of contextual classification

Constraints can be incorporated into the process like elevation, slopes, particular soil type, vegetation density, etc. The constraints act as an input to the knowledge process and object restrictions. This methodology has reported an increase of about 20 to 25 per cent in the accuracy of the classification of remote sensing images. The method has the flexibility to extend to irregular shaped objects, facilitating the analysis of complex terrain objects.

2.2 Fractal Characterisation

Quantifying the complex interrelation between these notion of size, generalisation, and precision has proven to be a difficult task, although several measures such as univariate and multivariate statistics, spatial autocorrelation indices, such as Morans I or Gearys C, and local variance within a moving window[3] provide some understanding of these interactions under given assumptions and within limits of certainty. An important area of research is the concept of fractals to determine the response of measures-to-scale and resolution[4]. Fractals embody the concept of self-similarity, in which the spatial behaviour or appearance of system is largely independent of scale. Self-similarity is defined as the property of curves or surfaces where each part is indistinguishable from the whole, or where the form of the curve or surface is invariant wrt scale.

Fractal structures have caught the imagination of the engineering and scientific community because of their beautiful and intricate patterns and also simplicity of formation. Thus, fractal structures contain repetitions, of a given shape on all scales. Therefore, fractals are said to be self-similar or scale-invariant. The concept of self-similarity gives rise to the generator initiator method of making geometric fractals through iteration. In this, an initiator is chosen and repetivity is applied at increasingly small scales to fill in the fine structure of the object. The use of fractals in describing or characterising aspects of the natural world, such as surface topography, is relevant to remote sensing. Modelling the natural world by monfractals is generally not sufficient and the emphasis should therefore be given to multifractals.

Studies are being carried out to understand the relationship between fractal dimension and resolution, fractal dimension and texture and effect of changes in the relation between fractal dimension and resolution on temporal images. Isarithm[5], variogram[2] and triangular prism[6] are some of the methods used to calculate the fractal dimension of a remotely sensed image.

For computing the fractal dimension, an image is considered a 3-D surface, and its complexity is expressed in terms of variability over space. Similar to a natural surface, such as a hilly terrain or flat plain, its complexity is a function of its vertical variability of pixel values. Hilly terrain has more ups and downs than a flat plain and, thus represents a more complex surface[7]. This surface complexity can be expressed quantitatively by the fractal dimension D. A featureless surface with no measurable complexity would yield a fractal dimension close to 2. An infinite variable or complex surface would yield a fractal dimension close to 3. A topographic surface will have a dimension[5] of around 2.2 to 2.3.

Dimension values for image surfaces have been reported to be much higher, and depending upon the types of landscapes examined[8], can be as high as 2.7 to 2.9. The isarithm method has been frequently used for estimating the fractal dimension of image data (Fig. 2). This method follows the

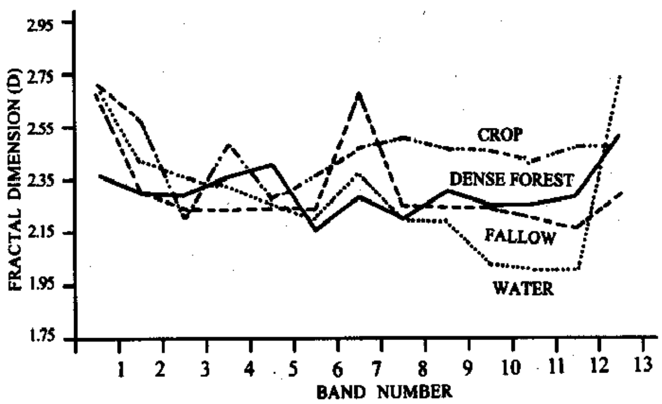

Figure 2. Fractal dimension of different features in IRS-P3, MOS-B bands.

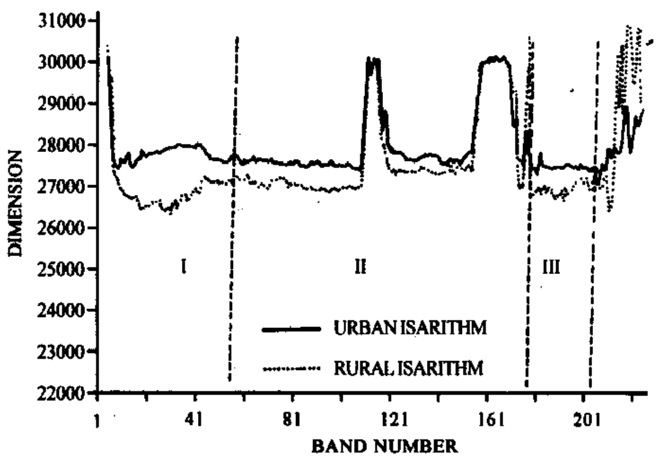

Figure 3. Fractal dimension of a typical urban and rural hyper-spectral imagery.

walking divider logic by measuring the dimensions of individual isarithm (isospectral reflectance curves) derived from the image surface. To compute the fractal dimension values of an isarithm, the image is divided into two regions; one above the current isarithm and the other below it. The length of the isarithm is represented by the number of the boundary pixels between the two regions. These boundary pixels are counted at various step sizes. The logarithm of the number of boundary pixels is then regressed against the logarithm of the step size, and the fractal dimension of the isarithm line is calculated based on the slope of the regression. The final dimension of the image is computed by averaging the D values of the isarithm that have high coefficient of determination ($R^2 > 0.9$) (Fig. 3).

3. NEURAL NETWORK SYSTEMS APPLICATIONS IN TARGET IDENTIFICATION

Neural and adaptive systems are used in many important engineering applications, such as signal enhancement, noise cancellation, classification of input patterns, system identification, prediction, and control. They are used in many commercial products, such as modems, image processing and recognition systems, speech recognition systems, front-end signal processors and biomedical instrumentation.

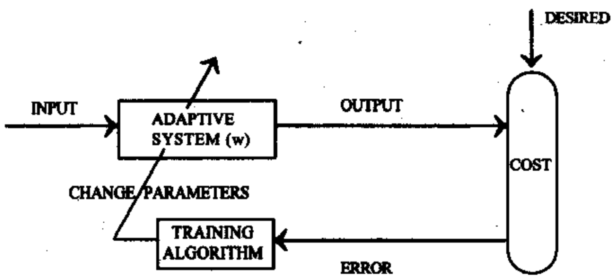

Figure 4. Adaptive systems

The leading characteristic of neural and adaptive systems is their adaptivity, which brings a totally new system design style (Fig. 4). Instead of being built *a priori* from specification, neural and adaptive systems use external data to automatically set their parameters. This means that neural systems are parametric. It also means that these are made aware of their outputs through a performance feedback loop that includes a cost function. The performance feedback is utilised directly to change the parameters through systematic procedures called learning or training rules, so that the system output improves wrt the desired goal (i.e. the error decreases through training).

The system designer has to specify just a few crucial steps in the overall process i.e. to decide the system topology, choose a performance criterion, and design the adaptive algorithms. In neural systems, the parameters are often modified in a selected set of data called the training set and are fixed during operation. The designer thus has to know how to specify the input and desired response data and when to stop the training phase. In adaptive systems, the system parameters are continuously adapted during operation with the current data. The system designers are now at a very exciting stage in neural and adaptive system development because

- They now know some powerful topologies that are able to create universal input-output mappings
- They also know how to design general adaptive algorithms to extract information from data and adapt the parameters of the mappers
- They are also starting to understand the prerequisites for generalisation, that is, how to guarantee that the performance in the training set extends to the data found during system operation.

Therefore, the system designers are in a position to design effective adaptive solutions to moderately difficult real-world problems. The basic element of a neural network is the processing node (Fig. 5). Each processing node mimics the biological neuron and performs two functions. First, it sums the values of its inputs. This sum is passed through an activation function to produce the nodes output values. An enhancement is to add a constant input to the summation at each processing node. The corresponding weight, called the bias weight, effectively controls the threshold level of the activation function. The processing nodes are organised into layers, each generally fully interconnected to the following layer (Fig. 6). However, there are *n* interconnections within a layer. In addition, there is an input layer that serves as a distribution structure for the data being presented to the network. No processing is done at this layer, one or more actual processing layers follow the input layer. The final processing layer is

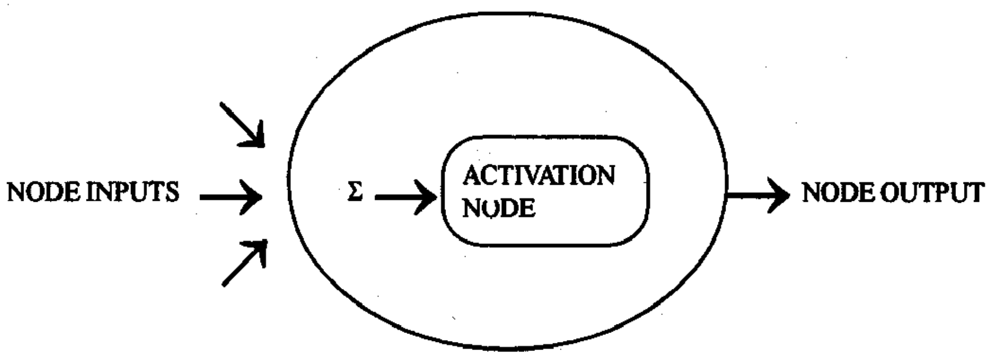

Figure 5. Inter structure of a neural network processing node

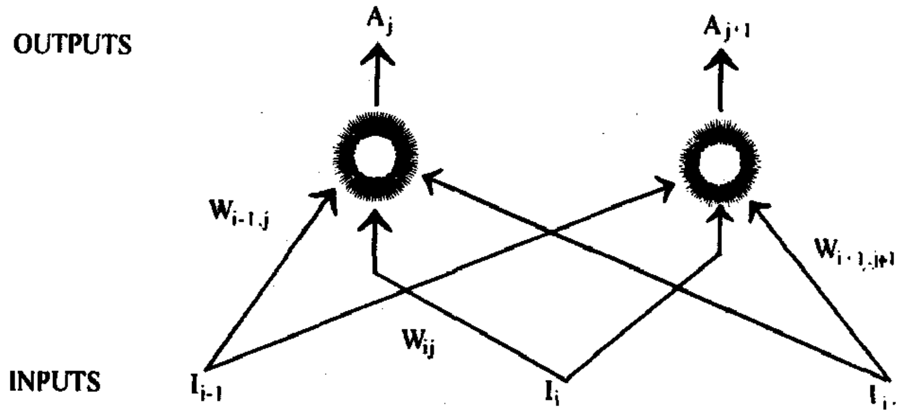

Figure 6. Generic neural network structure showing weight values and layer labels

called the output layer. Layers between the input and output layers are termed hidden layers. The interconnections between each node have an associated weight. When a value is passed down the interconnection, it is multiplied by the weight. These weight values contain the distributed knowledge of the network.

4. APPLICATIONS OF NEURAL NETWORK SYSTEMS TO MULTI-SPECTRAL IMAGES

The value of a pixel in each of the m bands of the multispectral image is presented to the input layer along with data for that pixel from k other sources (Fig. 7). These inputs are fanned out to the

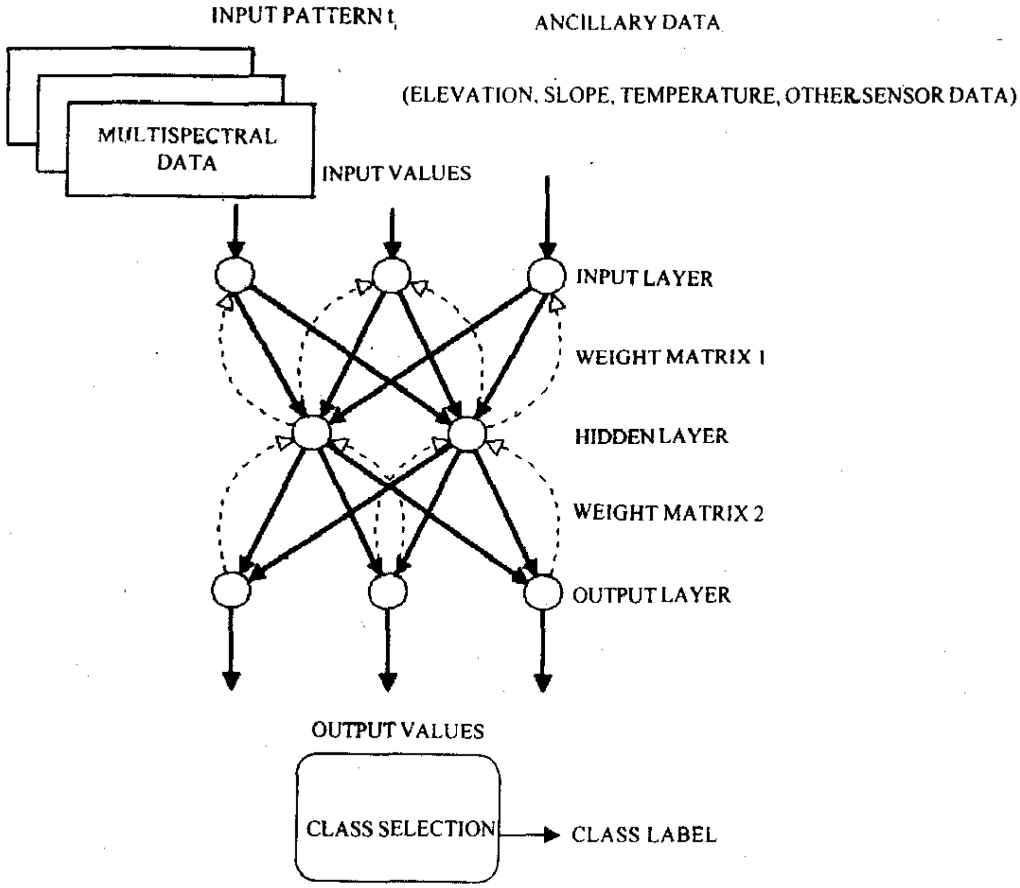

Figure 7. Typical back propagation network for target identification using multispectral imagery

first processing layer, the hidden layer. The numbei of nodes in the hidden layer are arbitrary and is usually chosen by experimentation. The outputs of the hidden layer are in turn fanned out to the final processing layer, the output layer. In this case, each output is used to represent one of zero possible groundcover classes. When the network is used in feed-forward mode for classification, the output values are usually continuous and class membership can be determined by a threshold or by choosing the highest output value.

A wide variety of neural network structures have been designed and applied to various applications[9]. The multilayer perceptron networks are the well known and widely used networks[10]. Another kind of network used in some studies has a cascade method of network construction that adds a hidden node, one at a time, during the training phase. As each hidden node is added, it is fully connected to all previous nodes. Once a hidden node is added and trained, its weights are fixed. The advantages of such a network is that it learns quickly, determines its own network size, and does not require the relatively slow back propogation learning algorithm.

5. HYPERSPECTRAL IMAGING

Imaging spectrometry refers to the imaging of a scene over a large number of discrete, contiguous spectral bands, such that a complete reflectance spectrum can be obtained for the region being imaged. This type of imaging is also known as hyperspectral imaging, in reference to the multispectral character of the data set. AVIRIS hyperspectral imager is one such example (Fig. 8) of an airborne imaging spectrometer which records at 224 spectral bands between 0.4 to 2.4 μm; each at about 10 nm spectral bandwidth.

The reflectance spectra of most materials on the earth's surface contain characteristic or diagnostic absorption features. Remote sensors capable of acquiring complete reflectance spectra over large areas offer a powerful tool for the study of the earth and its environment. Reflectance spectrum absorption features can be used to identify a number of important rock-forming minerals, and

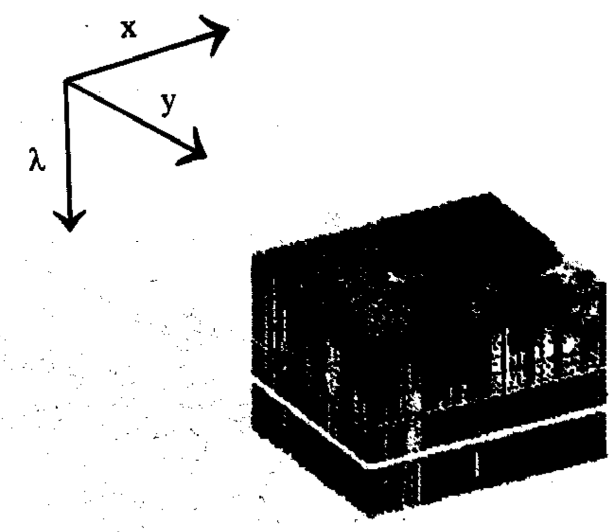

Figure 8. AVIRIS hyperspectral image data cube composed of individual images recorded at 224 spectral bands between 0.4 μm to 2.4 μm, each at about 10 nm spectral bandwidth.

have been used by the geologists for geologic mapping and studies of volcanoes. Spectral analysis techniques can be used for studies of vegetation, such as determination of effects of soil composition on trees by evaluating the spectral shift of the chlorophyll absorption band, determining leaf tissue water content, assessing forest fire damage. Using absorption spectra, coastal zone oceanic regions and other shallow waters have been monitored for everything, from oil spills and pulp mill effluent to schools of fish. Detection of many militarily important items, such as camouflage, thermal emissions and hazardous wastes, to name a few.

Hyperspectral imaging, like multispectral imaging is a passive technique (i.e. depends upon the sun or some other independent illumination sources) but unlike multispectral imaging, hyperspectral imaging creates a larger number of images from contiguous, rather than disjoint, regions of the spectrum typically with much finer resolution (Fig. 9). This increased sampling of the spectrum provides enormous increase in information. Many remote sensing tasks which are impractical or impossible with an multispectral imaging system can be accomplished with hyperspectral imaging. For example, detection of chemical or biological weapons, bomb damage

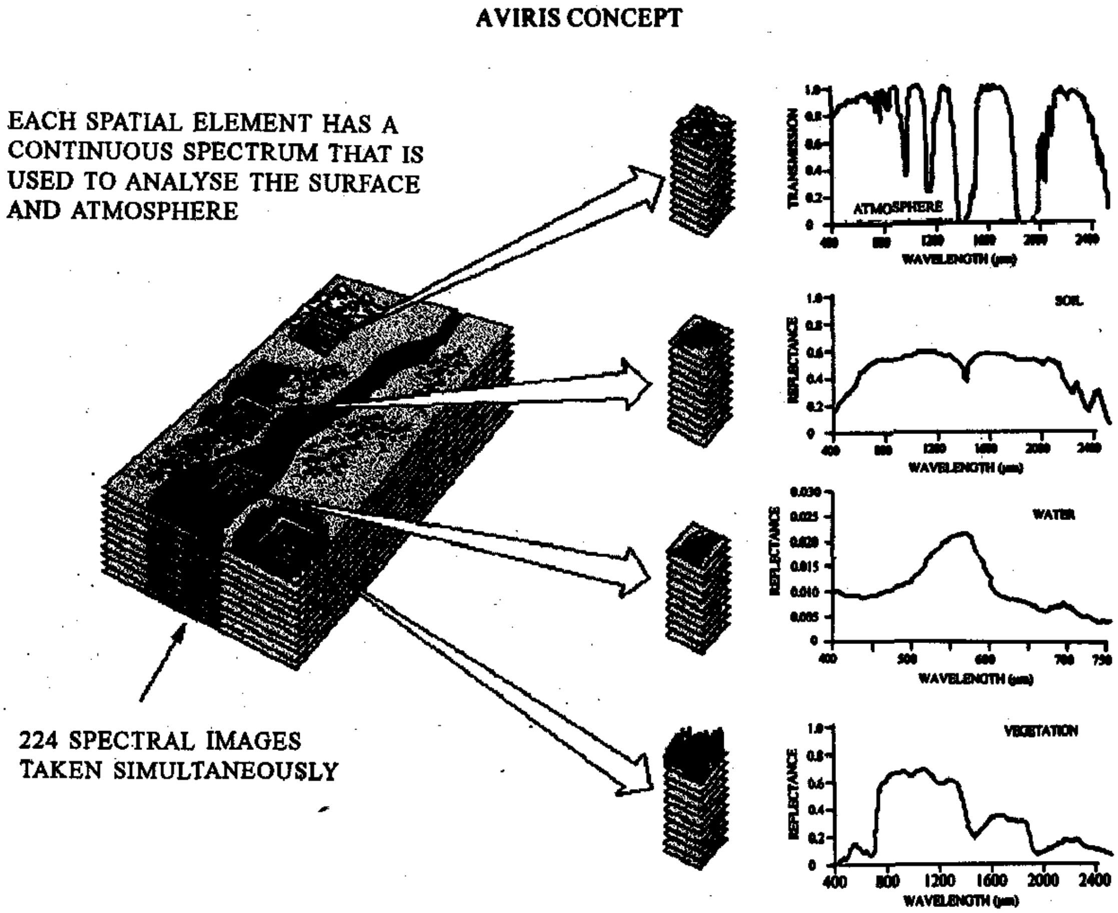

Figure 9. Hyperspectral imaging concept

assessment of underground structures, and foliage penetration to detect troops and vehicles are just a few potential hyperspectral imaging missions.

5.1 New Dimension

Hyperspectral imaging technique creates a large number of images of different regions of the spectrum:

- A stretch of desert, an expanse of sea, a blanket of forest, a checkerboard of crops.
- Familiar vistas: Scenic, but nothing out of the ordinary [(right analysis) (Fig. 10)].
- Vehicle hidden by camouflage, an area teeming with fish food, trees growing at different rates, fertile land underutilised, can be perceived.

By seeing what cannot be seen by the human eye, a hyperspectral imaging system gives resource managers – frontline commanders, farmers, urban planners, foresters, environmental analysts – a powerful tool to help classify features, measure productivity/yield and identify trends.

6. SAR INTERFEROMETRY

SAR Interferometry is a spin-off of microwave remote sensing. It finds applications in diverse fields, such as earthquake studies, volcano monitoring and glacier movement, land subsidence

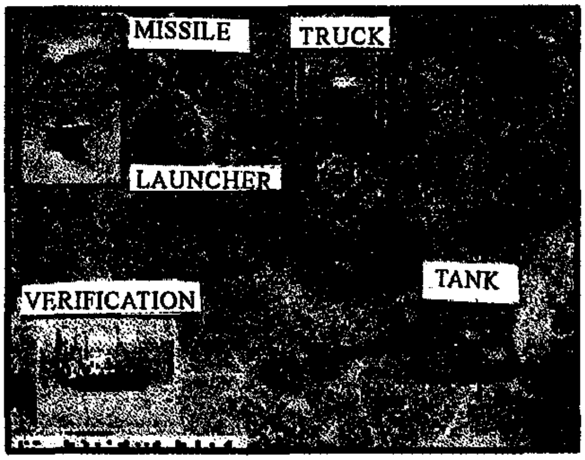

Figure 10. Detection of targets by hyperspectral imaging

due to mining and digital elevation models. There are several satellites in operation providing continuous data for SAR interferometry. ENVISAT and shuttle radar topography mission (SRTM) are dedicated for interferometry studies.

Microwave remote sensing has advantages over optical and thermal remote sensing techniques in view of its all-weather, day/night and penetration capabilities. There are two techniques in microwave remote sensing namely passive and active. Passive microwave remote sensing utilises the microwave radiation emitted by the earth's objects, whereas active microwave remote sensing has its own illumination, thereby making measurements of both intensity and phase of the returned signal. The intensity images are widely used for various earth resources studies. Recently, it has been realised that the phase information can also be used intelligently for several unique applications, which led to SAR Interferometry.

SAR Inferometry is a technique by which the phases of two SAR images of the same terrain are made to interfere to generate interference fringes. These two images can be taken simultaneously by an aircraft/satellite with two antennas separated by a distance known as baseline. This is referred to as single-pass interferometry (Fig. 11). SRTM has this capability. From Fig. 11, the terrain height $Z(y)$ can be obtained by

$$Z(y) = h - \frac{B^2 - \delta\rho^2}{2\,[\delta\rho - B\,\mathrm{Sin}(\alpha - \theta)]}$$

6.1 Shuttle Radar Topography Mission

The interferometry synthetic aperture radar (IFSAR) programme represents an effort to ingest and process high resolution elevation data produced through radar interferometry technique. The main source of these data is the SRTM, which is an IFSAR mission flown aboard the Space Shuttle in January 2000. The SRTM is a joint project of the National Imagery and Mapping Agency (NIMA) and the National Aeronautics and Space Administration (NASA) to map the world in 3-D. The IFSAR programme investigates characteristics

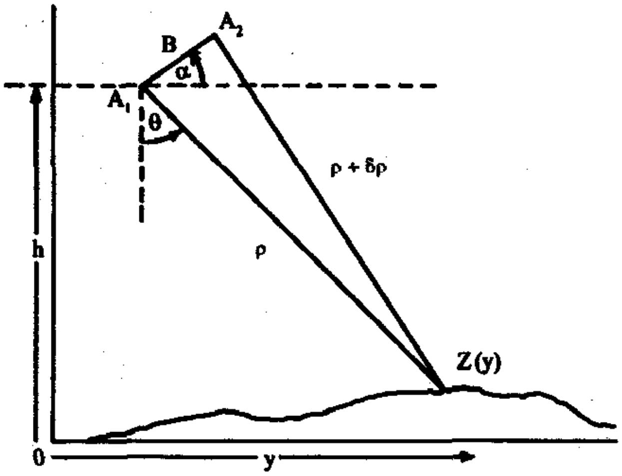

Figure 11. Basic imaging geometry for SAR interferometry. A1 and A2 represent two antennas viewing the same surface simultaneously, or a single antenna viewing the same surface on two separate passes.

of IFSAR elevation data along with methodologies for on-site validation and processing of raw terrain elevation data. This effort should result in an enhanced capability to process IFSAR and develop data sets that satisfy improved user requirements and provide worldwide digital terrain elevation data (DTED) coverage. The 11-day SRTM flight provided enough data for a digital model of earth that is more detailed than what is currently available. Successful completion of the SRTM data set will provide with coverage of most of earth's populated land areas, with three times better resolution than previously available. A key SRTM technology is radar interferometry. The SRTM components are shown in Fig. 12. SRTM will use single-pass interferometry, which means that the two images will be acquired at the same time – one from the radar antennas in the shuttle's payload bay, and the other from the radar antennas at the end of a 60 m mast extending from the shuttle. Combining the two images, a single 3-D image is produced. A key advantage to radar is that it can see the surface through clouds and in darkness. During its 11-day mission, Endeavour took high resolution radar images of 119 million km^2 (about 80 per cent) of the earth's surface (Fig. 13).

SRTM acquired data with 225 km swaths during the 11-day shuttle flight, imaging earth's entire land surface between 60° N and 56° S

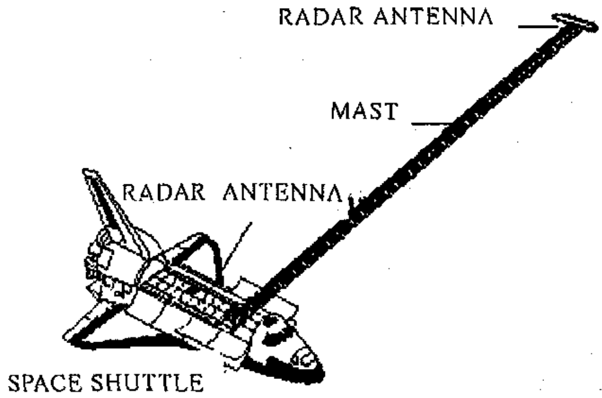

Figure 12. Shuttle radar topography mission components

latitude. The SRTM imaged 80 per cent of the earth's land surface and produced approximately 14,300 cells (1° × 1°) of terrain height data. This data will provide the means to meet the standing requirement to provide level II DTED specifications (30 m ×30 m) spatial sampling with 16 m absolute vertical height accuracy, 10 m relative vertical height accuracy and 20 m absolute horizontal circular accuracy). The resulting digital topographic map will form a homogeneous data set referenced to a uniform global geodetic datum. Data formats will be compatible with standard software and terrain analysis programs, tailored to the needs of the civil, military, and scientific communities.

Just any project that requires accurate knowledge of the shape and height of the land can benefit from this data. Scientific applications include geology, geophysics, earthquake research, volcano monitoring, hydrologic modelling, and co-registration of remotely acquired image data. Civilian applications include enhanced ground proximity warning systems for aircraft, civil engineering, land use planning, and line-of-sight determination for communications (e.g. cell phones). Military applications include flight simulators, logistical planning, traffic ability analysis, missile and weapon guidance systems, and battlefield management. The newest navigation and weapon systems require digital geospatial information in increasing amounts, more quickly, and on varying media, for successful mission operations.

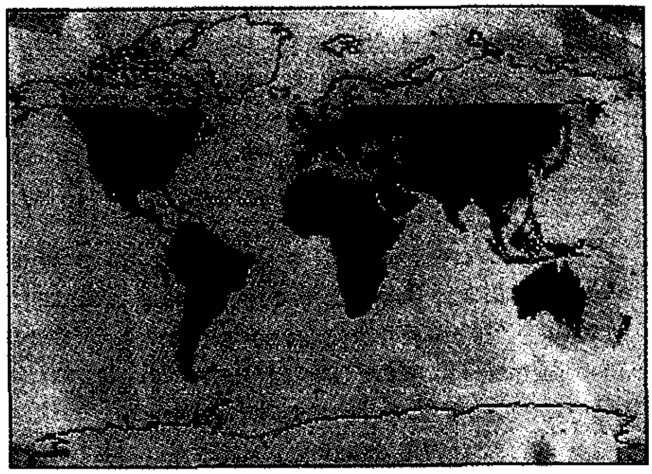

Figure 13. Shuttle radar topography mission coverage (shaded portions).

7. CONCLUSION

Remote sensing for strategic applications has come of age with a plethora of information ranging from hyperspectral to microwave, several advanced techniques in the areas of artificial intelligence and knowledge-based methods have made it possible to extract useful information from such abundant databases. The future is all about data mining in the domain of intelligent systems. Target identification and surveillance by digital video processing, image compression algorithms, image and intelligent data fusion methods are some of the emerging areas.

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