1. Introduction

It is common practice of man to classify the Earth into different regions. This is based on his observation and his ability to classify into different regions like forest areas, water bodies, hilly regions, constructed areas etc. To classify areas of larger dimensions remotely sensed data from satellites is to be used. Remotely sensed data are well adopted for monitoring and analyzing the behavior of different land covers and also the temporal changes occurring. This can be observed by periodically collecting the data and then comparing it with the previous data. Using various sensors, data is collected that can be analyzed to obtain information about objects, areas under investigation. The remotely sensed data is obtained through artificial satellites from various geographic and astronomical sources. The number of features in each sample in the multispectral data depends upon the number of channels the information is got. Data from different channels is be combined to obtain the detailed information about the body or area under observation. The remotely sensed multispectral imagery may be subjected to either supervised or unsupervised analysis. Our aim is to develop a self-organizing technique to classify remotely sensed images. The SOFM has the property to adapt to the density of input vectors at the same time preserving the topology of input space. The algorithm responsible for the formation of SOFM proceeds by initializing the synaptic weight in the network. Assigning them small values picked randomly from input space does this. Depending upon clusters generated by the SOFM regions are identified. This paper suggests a way by which self-Organizing Feature Map can be applied to classify the remotely sensed data.

2. THE IMPLEMENTATION OF SOFM

A SOFM is characterized by the formation of a topographic map of the input patterns in which neurons are indicative of statistical features contained in the input patterns. The SOFM works in three steps Competition, Co-operation and adaptation.

2.1 Competition

Here a discriminant function provides the basis for competition among the neurons. The winner neuron is called the best matching unit (BMU). If pattern \( X_i = (x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in})^T \), Where \( x_{i1}, x_{i2}, \ldots, x_{in} \) are the feature vectors of n dimension of \( i^{th} \) pattern. The weight vectors are
given by \(W_j = (w_{j1}, w_{j2}, \ldots, w_{jn})^T\). The weights are selected randomly from input set of patterns. Then the Euclidean distance between the \(j^{th}\) weight vectors and \(i^{th}\) pattern is given as:

\[
V_{ij} = \sum_{k=0}^{n} (x_{ik} - w_{jk})^2
\]

Best matching or the winner neuron is found using equation 1. The Neuron with minimum Euclidean distance is the best matching neuron. A continuous input space of activation patterns is mapped onto a discrete output space of neurons by a process of competition among the neurons in the network.

### 2.2 Co-operation

The winning neuron determines the spatial location of the topological neighborhood of the excited neurons. A neuron that is firing tends to excite the neurons in its immediate vicinity than those more far away from it. The Neighborhood distance between the best matching neuron and the adjacent neuron is found by Euclidean distance.

\[
d_{ij} = \sum_{k=0}^{n} (w_{ik} - w_{jk})^2
\]

\(i\) represents the winner neuron and \(j\) the adjacent neuron. \(d_{ij} = 0\) when \(i=j\) or neighborhood distance of winner neuron to itself is zero. The topological neighborhood is based on the rectangular function. The neighborhood \(h_{ij}\) between the winner and adjacent neuron is:

\[
h_{ij} = \begin{cases} 1 & \text{when } d_{ij} < \text{neigh} \\ 0 & \text{otherwise} \end{cases}
\]

Where \(\text{neigh}\) is the allowable neighbourhood size. The neighbourhood size is decreased at regular intervals.

\[
\text{neigh} = \frac{\text{neigh}}{\text{NEI}}
\]

Here \(\text{NEI}\) is a constant decrement operator.

### 2.3 Adaptation

After determining the neighborhood the winner and the neighbor neurons has to be trained cluster a given set of input patterns.

For neuron \(k\) the weights are trained as:

\[
W_{jx}(t+1) = W_{jx}(t) + (\alpha x h_{ij}(x) (x_{ik} - w_{jk}))
\]

\(h_{ij}(x)\) is the neighborhood size for pattern \(X_i\) as determined in equation 4. \(\alpha\) is the learning constant and it decrements at regular intervals. Here \(t\) is the number epochs during training.
3. ALGORITHM

1) Initialize the samples from the raw image to be processed. Normalize the samples by a maximum value. Assign weights from the input vectors.

2) Assign an input vector to the SOFM. The number of features per sample depends on the number of bands in the raw image.

3) Find the winner or best matching Neuron using equation 1.

4) Find the neighborhood using equations 2, 3 and 4.

5) Adjust the weight vectors of Neurons using Equation 5.

6) Repeat 2 to 5 for all the samples.

7) Repeat 6 until the required number of epochs is completed.

8) Obtain the number of classes and display the classification map.

4. Experimentation and Results

First Band                         Second Band                Third Band

Figure 1. Neptune great dark spot, Catalog # PIA 00052, Voyager 2.
(Courtesy of NASA Planetary Photo journal)

Figure 2. Classification Map of Neptune.

Following experiment is conducted on multispectral Voyager 2 data covering Great Dark spot of planet Neptune (as shown in figure 1). The image was shuttered at a distance of 2.8 million kilometers. The original image of 700 samples X 852 lines is condensed to 70 samples X 86 lines with 3 features. The image is about feathery white clouds that overlie the boundary of dark and light blue regions. The classification map shows the spot classified into 7 clusters as shown in figure 2 and 3.
5 Conclusions

In this article we have described an unsupervised method of clustering involving self-organizing feature method. The procedure has been successfully applied on many multispectral images. We are able to detect different regions and percentage cover on the classification map. We have successfully applied it on both geographic and astronomical data.

6. References


