RECOGNITION AND INVENTORY OF OCEANIC CLOUDS FROM SATELLITE DATA USING AN ARTIFICIAL NEURAL NETWORK TECHNIQUE

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SUMMARY

The use of satellite remote sensing provides the possibility for monitoring the genesis and evolution of oceanic clouds. In order to link cloud genesis and dimethylsulphide production it is necessary to develop a method for accurately classifying and extracting the properties of cloud fields in imagery. An experiment is reported in which an artificial neural network has been used to identify the main types of clouds found in NOAA/AVHRR imagery of the northern Atlantic ocean. The method is based on the use of an unsupervised pattern recognition approach: the topological (or self-organising) map neural network. Such a network has been trained with 362 examples of 40x40 cloud fields extracted from imagery and has been used to provide 25 different cloud classes.

1. INTRODUCTION

The Institute for Remote Sensing Applications of the Joint Research Centre possesses a large dataset of daily raw satellite images from the NOAA Advanced Very High Resolution Radiometer (AVHRR) spanning more than a decade with coverage over a significant portion of the eastern Atlantic Ocean [6°-30°E, 0°-40°N]. These images with 4km. 'Global Area Coverage' resolution in 5 spectral channels (2 visible, 1 near infra-red and 2 thermal infra-red) have been used in the past to produce an archive of sea surface temperature data for coastal upwelling studies. However in principle this same raw dataset could be used also to categorise and make inventories of clouds over the ocean. This could lead to studies of time trends and possible linkages to cloud generation effects such as the phytoplankton-created Dimethylsulphide (DMS).

In order to study possible links between DMS production and cloud generation or modification, it will be useful to make accurate maps of cloud types and amounts over the very long time period permitted by the JRC's AVHRR dataset. However the recognition and categorisation of clouds in satellite images is a non-trivial problem. The visible channels of the AVHRR provide cloud reflectance information related to optical thickness and the infra-red channels provide brightness temperature information which is related to cloud height. However the recognition of cloud types also depends on their spatial textures which can also be extracted from imagery. The cloud recognition problem in satellite images is thus a difficult discrimination problem involving multi-parameter pattern recognition. In our recent work at the JRC we have demonstrated the potential value of artificial neural networks in recognition tasks of this complexity e.g. for classifying complex satellite image data of land surfaces (1). Besides their capability for solving complex pattern recognition problems, neural networks offer the additional possibility of direct encoding in parallel computer hardware allowing very fast analysis of large data archives.

The application of neural networks to cloud classification is not new to this study and has already been reported in (2) and (3). In both of these applications, neural networks have been used to carry out supervised classification. Examples of particular image classes have been used to train an artificial neural network to encode the cloud class characteristics. The network can then be used for classification. In the applications reported multi-layer perceptron networks were used based on the backpropagation training algorithm (4).

For oceanic cloud recognition however, for DMS studies, we have chosen a different approach. The NOAA/AVHRR dataset provides a very extensive volume of images from which training examples could be extracted. However instead of manually extracting and naming class examples, we have chosen an unsupervised neural network approach to learn the characteristics of the main classes which can in principle be extracted from the dataset. This is effectively a data clustering procedure -i.e. we allow the neural network algorithm to identify the most meaningful types of cloud fields present in typical AVHRR imagery of the north east Atlantic Ocean. We do not wish to make an arbitrary manual classification of clouds in the imagery at the beginning in order to train a supervised classifier. If the unsupervised approach performs well, it will be possible at a subsequent stage to label the prototype cloud classes derived by the neural network approach and to use those prototypes as a basis for classification of new cloud field data.

2. THE TOPOLOGICAL MAP NEURAL NETWORK

The T-Map neural network algorithm (also called the self-organising map or Kohonen map) is an unsupervised pattern recognition technique (5), (6). For our application it provides a relatively easy way of using both radiance and texture information present in cloud field images.

The T-map consists of two layers of neural nodes. The first layer has one neuron node per component of input feature vectors. The second layer is a two-dimensional array of competitive neural nodes each of which will represent a prototype pattern learned from a training data set. This second layer effectively becomes a 'map' showing the natural relationships between the patterns that are given to the network.

All interconnections in the network go from the first layer to the second. The two layers are fully interconnected, thus each node of the input layer is connected to all of the nodes in the second (competitive) layer. Each interconnection has an associated weight value -see figure 1.

The nodes in the second layer each form weighted combinations of the outputs from the first (input) layer. Initially the weights between the nodes in the two layers are random but they are progressively modified during an iterative training procedure to encode a mapping from the input feature space to the classification space. The weight values are updated during the training procedure as follows:

Suppose an n-dimensional input feature vector **E** is fed to the n-node input layer of the network and is denoted as:

$$\mathbf{E} = \{e_1, e_2, e_3, \ldots, e_n\}$$

Let the set of weights **W** associated with the interconnections be denoted as:

$$\mathbf{W} = \{w_{i1}, w_{i2}, \ldots w_{in}\}$$

where 'i' denotes the ith. node in the competitive layer.

When pattern **E** is presented to the network the extent to which it matches the weights associated with each node in the competitive layer is computed. The match extent for node 'i' is $\| \mathbf{E} - \mathbf{W_i} \|$ which is the difference between the vectors **E** and $\mathbf{W_i}$. The node in the competitive layer for which this value is the smallest is the winner.

After the winning node has been identified a procedure is invoked to find the neighbourhood around it denoted as N_c. This consists of nodes close to the winning node 'c'. The size and shape of the neighbourhood can be selected by the user. Its size is normally reduced as training proceeds. Weights are then updated for all neurons that are in the neighbourhood of the winning node according to the equation:

$$\Delta w_{ij} = \alpha(e_j - w_{ij}) \text{ if node 'i' is in the neighbouhood, otherwise } \Delta w_{ij} = 0 \text{, and}$$

$$w_{ij\,new} = w_{ij} + \Delta w_{ij}.$$

This adjustment results in the winning node and its neighbours becoming more like the input pattern. The winner then becomes more likely to win if the same or a similar input pattern is presented at a later stage. The parameter 'α' is the learning rate which is also normally decreased during the training process.

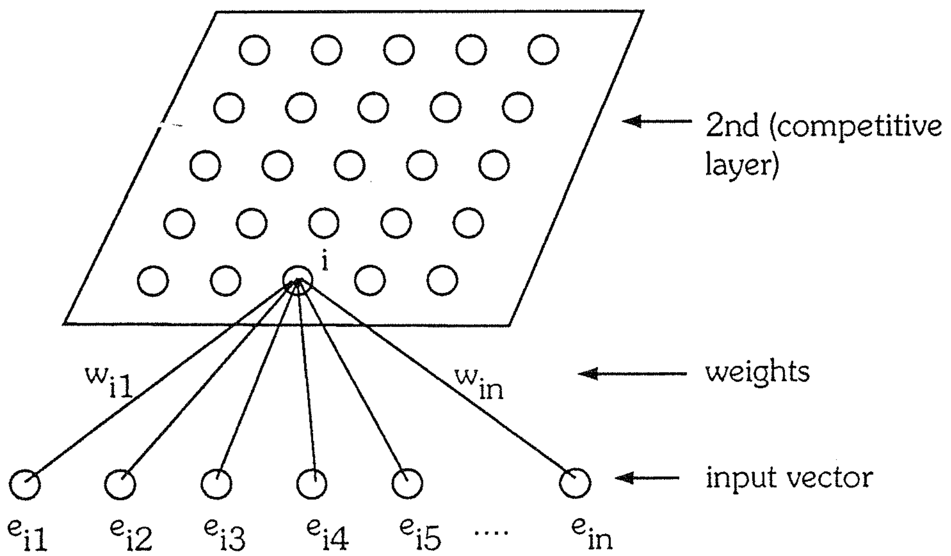

Figure 1. Architecture of the topological map network.

As the training procedure runs, the weights associated with the output layer begin to take on the characteristics of the main clusters of input feature vectors. Hence the main types of cloud fields present in the dataset begin to emerge as prototypes.

For identifying cloud field prototypes we have used a 3200-component feature vector (i.e. all pixel values in a 40x40 pixel window in both a visible and an infra-red channel) and have used a 5x5 array of nodes in the second layer to extract 25 prototype cloud fields. Both spectral and spatial information are present in the input feature vectors.

3. CLUSTERING CLOUD FIELDS USING THE T-MAP APPROACH

In order to extract the significant types of oceanic clouds which can be identified in NOAA AVHRR imagery, a total of 362 sample cloud fields were extracted from the JRC's Atlantic Ocean dataset and used to train a T-map (7). The image data were initially radiometrically calibrated and adjusted for solar zenith angle variations etc. The T-map algorithm used in these experiments was provided by a commercial neural network package 'MIMENICE' (Mimetics corporation) on a Sun SparcStation-2 computer.

Figures 2 - 4 show the 5x5 array of prototype cloud fields at the second (output) layer of the T-map. Figure 2 shows the output of the neural network before training -i.e. all cloud prototypes are blank. Figure 3 shows the output of the neural network after 30 training iterations. Already at this stage the network has been able to extract quite well the characteristics of 25 prototype cloud fields. Figure 4 shows the final cloud field prototypes at the end of training after 1530 iterations through the training set. The network has now learned the characteristics of 25 prototypes and very little change was noted between the last few iterations prior to this. Each prototype is shown as a pair of images- the one on the right is in a visible channel and the one on the left is in a thermal infra-red channel. Figure 5 gives an interpretation of the network output. These prototypes indicate the 25 most significant types of cloud fields which can be extracted from a typical AVHRR dataset. The prototypes include cumuliform, stratiform and cirriform clouds.

4. CONCLUSIONS

Satellite remote sensing has the potential to allow us to monitor the genesis and evolution of cloud patterns over large oceanic areas and through long periods of time. At the present time, one of the greatest challenges in linking DMS production and clouds is the problem of adequately identifying cloud types in satellite imagery and measuring their properties and then establishing links with plankton data available from other satellite datasets. Alongside the recognition problem there is the difficulty of handling the large volumes of satellite data involved. Here we have shown that artificial neural networks, of the topological map type, can be used as a recognition tool besides allowing us to process large datasets quickly. This research is still at an early stage, but if the T-map can be used to pick out more classes of clouds with a greater variety of properties, and if it can be encoded for parallel computing, then operational use for application to the DMS problem will be possible.

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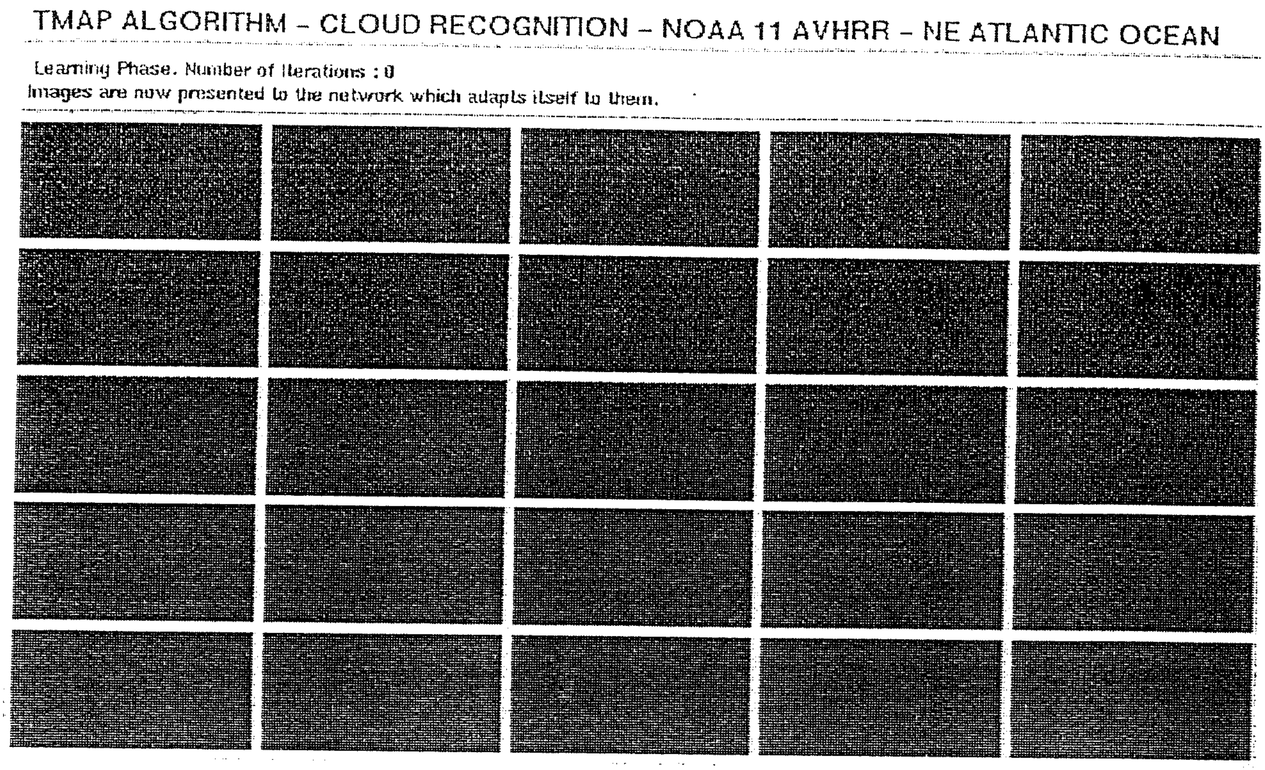

Figure 2. Prototype cloud fields from the T-map at iteration 0.

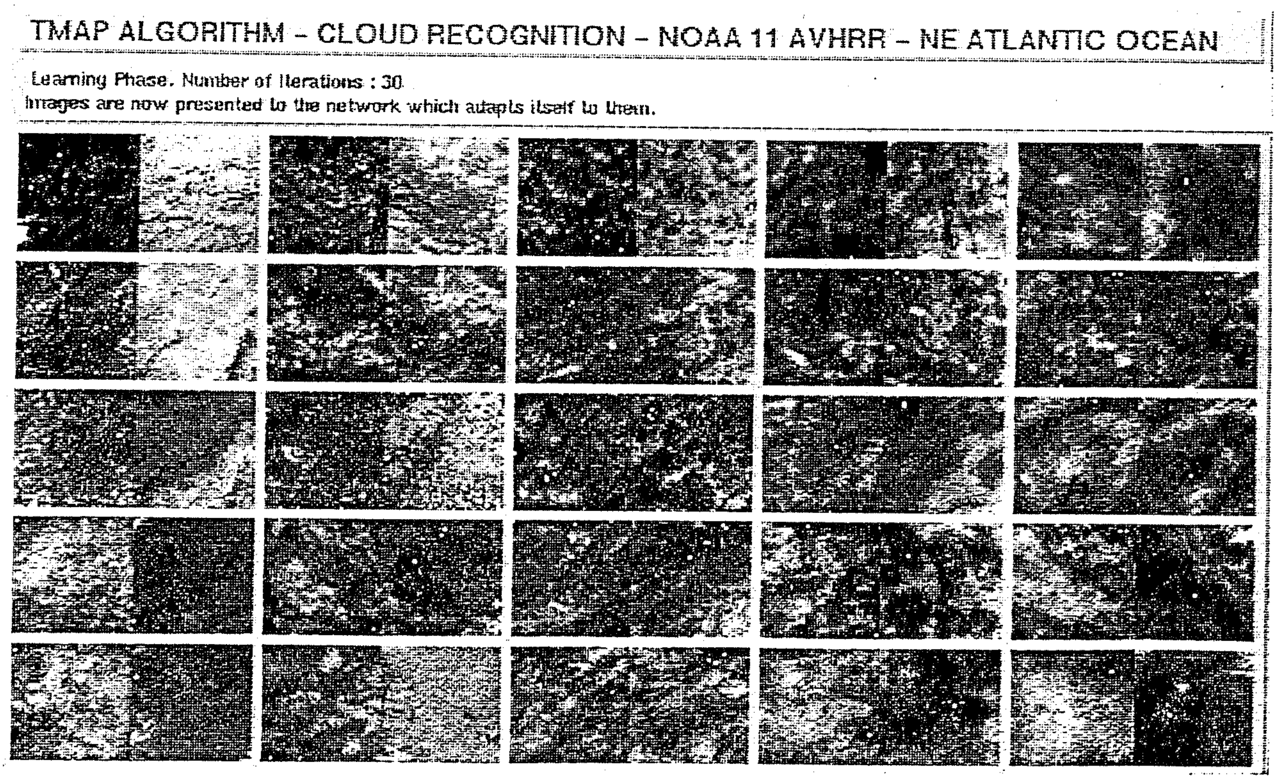

Figure 3. Prototype cloud fields from the T-map at iteration 30.

Εργασία 2.20

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