8. CLOUD DETECTION IN MULTI-SPECTRAL NOAA-AVHRR DATA USING MULTI-LAYER PERCEPTRONS : A PILOT STUDY

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ABSTRACT

Following some of the recommendations proposed by the International Satellite Cloud Climatology Project (ISCCP) for the improvement of cloud detection in remote multi-spectral radiance measurements, a pixel classification method using multi-layer perceptrons (MLP's) is presented for the detection of clouds in multi-spectral Advanced Very High Resolution Radiometer data (NOAA-AVHRR). Adaptive MLP-filters are applied to local features extracted from all spectral channels. We show that MLP-filters classify different cloud and surface types in good consistence with the manual classification by meteorologists. Basic problems related to sunglint and semi-transparent cloud formations remain unsolved as expected. Miss-classification in obscured image regions due to low sun elevation could be solved partially by retraining the filter in the IR-channel only.

INTRODUCTION

Since satellite radiance measurements became available at the end of the 70's, the need for automated cloud detection has widely been stressed, e.g. for climatology studies, and many cloud analysis algorithms have been proposed in literature. Six of these algorithms have been compared for the first time in 1981 by the International Satellite Cloud Climatology Project (ISCCP) and found to be good for the detection of specific cloud formations only (GOES-East and TIROS-N radiation data). This study enabled ISCCP to define a state-of-the-art algorithm composed of a sequential series of analysis steps. An important initial step in this algorithm was to detect the clear radiances from each satellite image, the last step included a bispectral threshold procedure to detect the cloud fractions. The cloud classification itself was done by comparing the cloudy radiances with those obtained from radiative transfer models with a simplified treatment of clouds.

This ISCCP study finally concluded by defining four scientific research recommendations to improve digital cloud analysis [1], being:

1. histogram and other statistical methods,
2. multichannel radiative transfer methods,
3. cloud morphology statistics,
4. extraction of additional cloud properties from satellite observations.

With modern meteorological satellites, the resolution of radiance measurements increased and more radiation channels became available. But although many efforts have been made to improve the accuracy of cloud detection following these ISCCP recommendations, the results obtained with conventional statistical methods are not yet satisfactory for many cloud conditions [1-9].

This observation motivated us to start a pilot study on cloud detection in NOAA-AVHRR (Advanced Very High Resolution Radiometer) data following an alternative approach: the use of neural network based adaptive local filters. The choice of the multi-layer perceptron (MLP) [10] as an adaptive local filter model for cloud detection was inspired by the results obtained during previous studies on (synthetic) texture classification with the same type of filters [11]. From literature and from these studies we know that 3-layered MLP's can be trained to classify pixels, e.g. assign labels to pixels in an image, starting from a set of pre-classified examples. MLP-based pixel classifiers are local filters which can be applied directly on the grey values of image segments or on a set of pre-defined features extracted from these segments. The training set is composed of a set of local image segments or a set of features extracted from these segments, together with the corresponding label (class) to which the central pixel of these segments belongs. Unknown pixels are classified using the grey values present, or features extracted from new segments with the same dimension. This property makes adaptive MLP-filters attractive, even fairly general (although not generic) for a whole set of local classification problems (texture recognition, boundary detection, segmentation,....)[11, 12].

Our previous studies on MLP-based texture classifiers could therefore easily be mapped on the problem of cloud recognition in satellite images. This article reports on results obtained with NOAA-AVHRR calibrated images. We preferred NOAA rather then METEOSAT satellite data to start the pilot project for two main reasons:

• the resolution of NOAA satellite images (1 km²) is much higher than the resolution of METEOSAT images (25 km² for the IR and water vapour channel) revealing more information on cloud morphology. The use of high resolution radiation data meets the fourth ISCCP recommendation (see above) and makes the generalisation of MLP-based texture classifiers for cloud detection more straightforward.

• the number of radiation channels of NOAA images is higher then the number of radiation channels of METEOSAT images. An exhaustive study on the definition of statistical relevant local features extracted from the four (for NOAA10) or five (for NOAA11) radiation channels for the purpose of cloud recognition has been done by K. Karlsson and E. Liljas of the Swedish Meteorological and Hydrological Institute (SMHI) in 1990 [2, 3]. Using the same features as input data for the MLP classifier, we met the second ISCCP recommendation (see above).

We obtained NOAA-AVHRR data from the Royal Meteorological Institute of Brussels (KMI-IRM) - Belgium. NOAA10-AVHRR multi-spectral images have a dimension of 2840 x 2880 pixels in four channels:

channel 1: visible-orange
channel 2: red-near IR
channel 3: IR 3.55 to 3.93 micron
channel 4: around 10-13 micron

Following the advice of E. Liljas [2, 3], we learned a MLP-filter to recognise 10 radiation classes (see Table 1) starting from nine input features: the grey value of the pixel itself for channels 1, 2, 3 and 4, the mean grey value of image segments of 11x11 pixels for channel 4 and the variance of grey values observed in image segments of 5x5 pixels for channels 1, 2, 3 and 4. Although the MLP-filter assigns class labels to individual pixels, spatial and spectral correlations of the grey values of the environment of each pixel are taken into account intrinsically using these features as input data.

class nr	class	pseudo colour code
01.	open sea...	black
02.	land (snow free)................................	dark blue
03.	snow cover.......................................	light blue
04.	low convection (e.g. stratocumulus)	blue-green
05.	low stratus	light green
06.	altocumulus, altostratus......................	green

07. cumulus..	blue
08. nimbostratus, cumulonimbus..............	red
09. thin cirrus..	rose
10. thick cirrus...	yellow

Table 1 Radiation classes to be detected in NOAA-AVHRR images (according to E. Liljas and K.G. Karlsson, [2, 3]) and the corresponding pseudo-colour code used in the classified picture examples.
An appropriate training set was obtained using the expertise of meteorologists (KMI-IMR) who classified manually radiation regions representing good examples of the 10 classes mentioned in Table 1 on an image captured in April 1991 by NOAA10 (orbit #23973-30/4/91 07:15:16). This month of the year guarantees good visual information.

RESULTS

The MLP-filter was composed of a 3-layered network architecture containing 9 input units (representing the nine input features), a variable number of hidden units and 10 output units (representing the 10 classes to be detected). The network has been adapted to 500 samples of the available training set using the common gradient backpropagation (GBP) learning procedure [2]. A momentum term was added to the basic GBP-equation (delta-rule) to stabilise the convergence of the iteration procedure:

$$\Delta\omega_{ji}(t+1) = \lambda\delta_j x_i + \alpha\Delta\omega_{ji}(t)$$

The term on the left side of the equation indicates the update of the activity value between neuron i and j after t iterations. The left term on the right side of the equation represents the generalised ∂-rule [2] and the right term the momentum term. The parameters _ (learning factor) and a (momentum factor) are optimized experimentally (see further).

1. DYNAMIC BEHAVIOUR OF THE MLP-FILTER DURING TRAINING.

The dynamic behaviour of gradient backpropagation used as a learning procedure for MLP's is well documented in literature for a variety of case studies [2]. No local minima have been observed during our experiments (Fig.1), but we detected problems of over-training of the network after +-7000 iterations, e.g. the global classification performance on the test set started to decrease (global error increased), while the global classification performance on the learning set was still increasing (global error was still decreasing) indicating that the MLP-filter started to adapt itself to irrelevant details of the learning set (Fig.2). We were forced to trigger the convergence process by following the behaviour of the MLP-filter on the test set and to interrupt the learning procedure once the network had obtained an optimal classification score on this set.

2. GENERALISATION ON THE SAME IMAGE (APRIL 1991, NOAA10- ORBIT #23973-30/4/91 07:15:16).

The training set (500 samples) represents only 0.01% of the total amount of pixels in the image. This allowed us to apply the trained MLP-filter on the same April image in order to extract useful information on the generalisation performance of the filter. How can the classification performance be measured numerically however ? Due to the high dimension and the multi-spectral nature of NOAA-AVHRR images, it is unreasonable, unlikely and even impossible to ask a meteorologist to classify the 4 channels of a whole NOAA-AVHRR image by hand on a pixel level. Such a pre-classified image would also contain many classification errors due to the presence of uncertain cloud boundaries, ambiguous radiative properties (e.g. sunglint and semi-tranparant cloud coverage) and the non-consistent cloud classification in the 4 channels (different cloud labels assigned to the same image regions in different spectral channels).

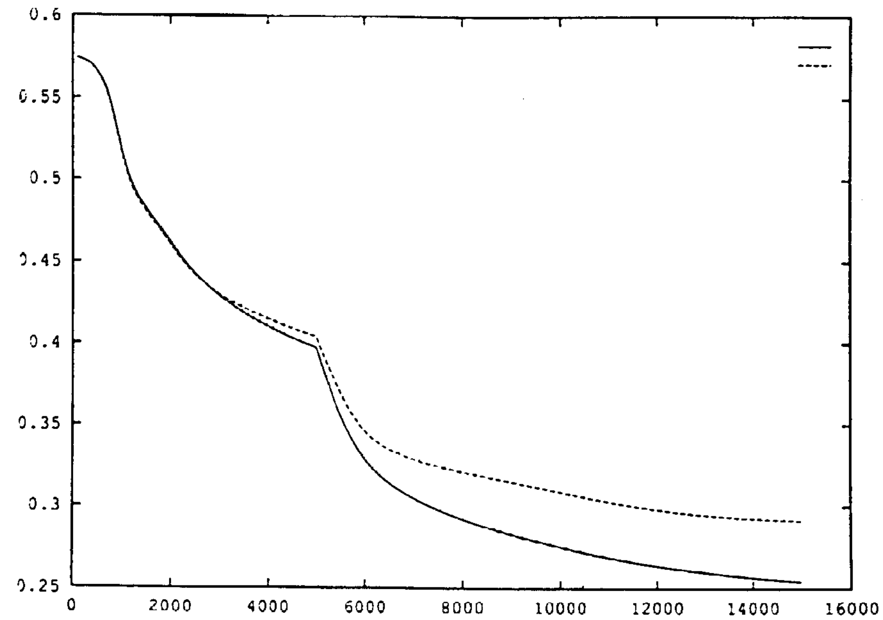

Figure 1 : Convergence profile of the MLP-filter (10 hidden neurons) during training on the April-image (NOAA10-orbit #23973-30/4/91 07:15:16): evolution of the LMS-error on the test set and learning set versus the number of iterations. After +-4500 iterations, the learning factor (lambda = 0.001) has been changed to 0.03 to speed up the convergence (momentum factor, alfa = 0.7).

Therefore, the generalisation results in the total image had to be evaluated qualitatively by meteorologists. The global classification performance on the same April-image with a MLP-filter composed of 10 hidden neurons was experienced to be very good (Pict.1 p.191). Some classification errors were detected however due to uncertain network decisions on the cloud boundaries, the presence of superimposed layers of different cloud types and semi-transparent cloud coverage, and the problem of sunglint (Pict.2 p.191). The reason for certain classification errors must be found in the presence of erroneous pre-classified pixels in the training set, and, to a lesser extent, in the presence of noise due to the radiation sensor. As a conclusion of this experiment we can also state that the classification score of the MLP-filter is not the same for all the cloud types (Fig.3). This property was observed for conventional classification algorithms too by ISCCP.

Although we do not have an objective criterion to measure cloud classification scores adequately, we have computed numerically the generalisation performance of the MLP-filter on pixels of the pre-classified regions from which the learning set has been extracted. Depending on the number of hidden neurons considered, we obtained 71.0% correctly classified pixels for 10 hidden neurons (typically 1 day computing on a SUN SPARC II) and 76.1% correctly classified pixels for 30 hidden neurons (typically 1 week computing on a SUN Sparc II). Experiments with more learning samples (5000) showed that the overall classification performance did not improve if the learning time (see above) is kept reasonable. We experienced these numerical classification scores as being rather low in comparison with the qualitative evaluation scores given by meteorologists. A possible explanation for this discrepancy may be that although many local classification errors are made by the MLP-filter (and detected by numerical evaluation procedures), the global structure of cloud formations is well preserved and recognised in a first order by the human eye (Pict.1). This observation inspires us to do future research on the correction of local miss-classifications using the classification labels assigned in the neighbourhood of each pixel (e.g. by using morphological operators).

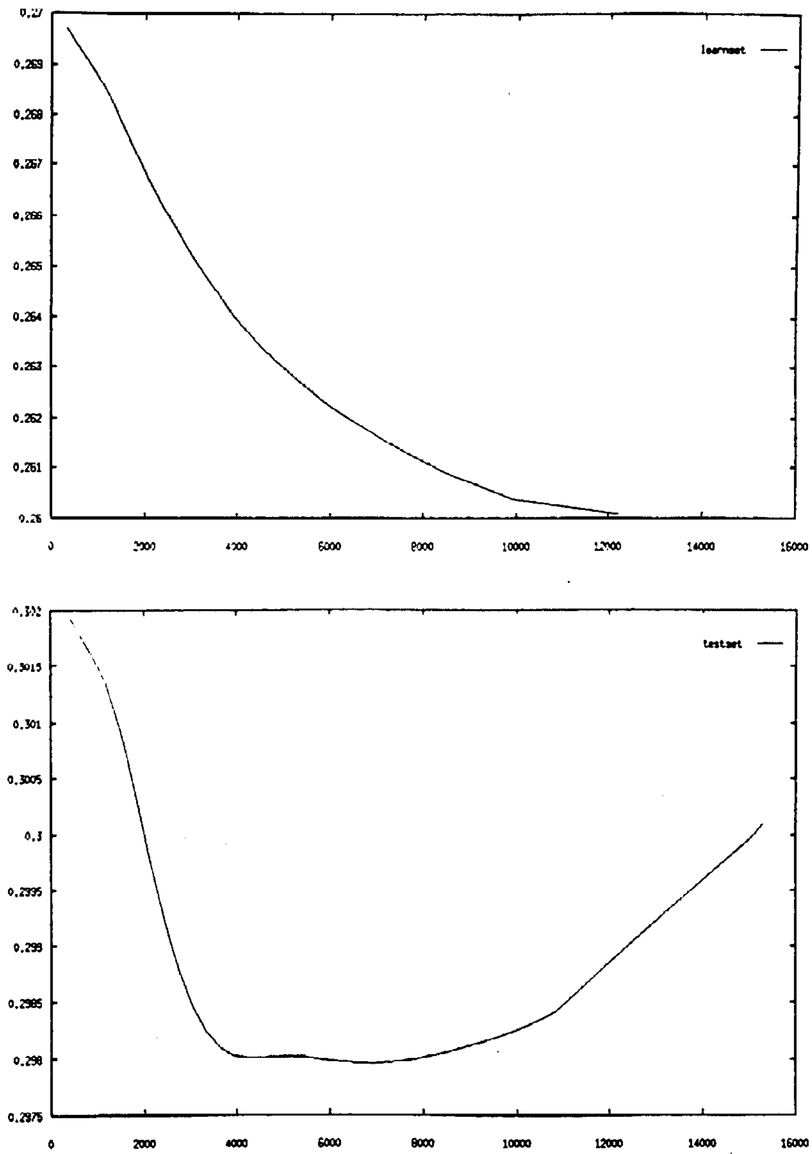

Figure 2 : Overtraining: evolution of the global error on the learning set (upper graph) and evolution of the global error on the test set versus the number of learning cycles (MLP with 10 hidden neurons).

3. GENERALISATION ON AN IMAGE CAPTURED IN NOVEMBER 1991 (NOAA11-ORBIT #16324 25/11/1991 12:46:54).

The same MLP-filter (trained on an image of April) has been applied to an AVHRR image captured in November 1991 by NOAA11 (orbit #16324 25/11/1991 12:46:54). Important classification errors can be predicted beforehand if we apply the same connectivity matrices adapted to the spectral channels of an image captured in April to those of an image captured in November. The sun elevation in November is very low giving less or no visual information in important regions of the image. Also, the ground temperature and therefore the background radiation are completely different in April and November. More-

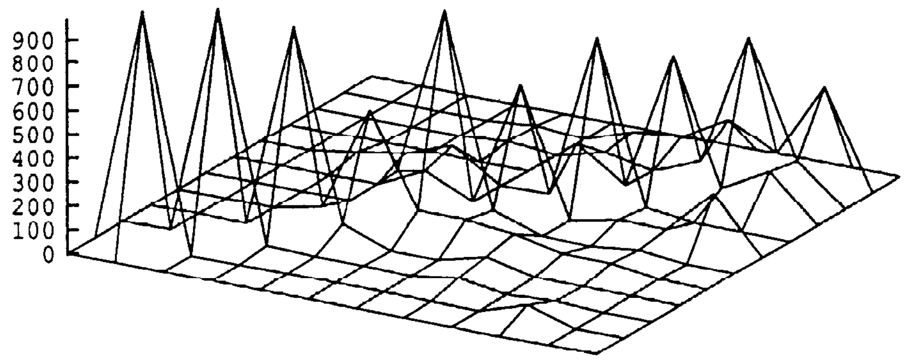

Figure 3 : Classification score of a MLP-filter (10 hidden neurons) as a function of the class type (horizontal axes)

over, the spectral intervals of the NOAA11 channels are not exactly the same as for NOAA10. The classification performance of the network has been verified to be very good by experts of KMI-IMR however in those parts of the image where visual information was available (Pict.3 p.192), but (as expected) very bad in those parts of the image where no visual information was available due to a low sun elevation (Pict.4 p.192). For these obscured regions, we trained a new MLP-filter on the IR-channel 4 only using 3 features: the local grey value, the mean grey value of a local segment 11x11 pixels and the variance observed in a segment of 5x5 pixels. The global classification performance of this MLP-filter was found to be acceptable by meteorologists (Pict.5 p.192).

CONCLUSION AND FUTURE RESEARCH

This pilot study showed that MLP-based local adaptive filters applied to relevant statistical features extracted from the different spectral channels of NOAA-AVHRR radiation measurements are performing well with respect to the classification of local radiation properties in terms of different cloud coverages and earth surface observations. Local classification errors could probably be solved using morphological operators acting on the classified images. Basic classification problems due to sunglint and semi-transparent cloud formations remain unsolved for the time being. Classification problems relating to a low sun elevation can partially be avoided by training the MLP-filter in the IR channel only. Further research on the influence of seasons on the generalisation performance of a given MLP-filter is mandatory however.

We experience the need for an objective evaluation criterion for cloud detection to measure the generalisation performance of MLP-filters on different images and to compare the classification results obtained with MLP-based filters with those of conventional classification algorithms.

Important future research for the evaluation of the power of MLP-filters for cloud detection in satellite images will consist of applying these type of filters directly to grey values in order to see to what extent they are able to extract statistically more relevant features then those proposed by SMHI for the detection of cloud formations in NOAA-AVHRR images. If this task would be too complex to be solved by GBP, we could initialise the filter close to a global solution of the classification problem before training by injecting connectivity values obtained during this pilot study.

Other neural network architectures for the detection of clouds in METEOSAT images are under investigation at the European Space Agency, European Space Operations Centre at Darmstadt - Germany.

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The authors wish to thank Prof. A. Quinet and Dr. Ir R. Heylen and all the members of the Electronics Department and Forecasting Department of the Royal Meteorological Institute (KMI - IMR) for their collaboration.
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