Neural Network Based Cloud Classifier

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Abstract

It has recently been popular to use neural network based classifiers in remote sensing. The reported results are usually based on a very limited data set. This paper concerns the experiences from the cloud classification scheme. The experiences are based on a data set of several hundred images. The classification is based on Self-Organizing Maps (SOM), which are fine-tuned by the Learning Vector Quantization (LVQ). The classification is done in two phases, the clouds are first screened and then classified. The classifier is capable of classifying satellite images taken round the year, during day and night. The classifier is fully automatic, and it can be adapted to changing situations with new examples. The benefits of this approach are rapid prototyping, adaptivity, and in high degree unsupervised learning.

1 Introduction

High-resolution satellite images received from weather satellites are used for weather forecasting and medium term prediction. There are several weather satellites but the NOAA-11 and the NOAA-12 satellites are used in the Nordic countries. The automatic interpretation of satellite images has been studied in two projects in the Laboratory of Computer and Information Science at Helsinki University of Technology since 1991. In the first project the cloud classification was required over the Nordic Countries. In the second project the cloud cover and the cloud classification were required but only for some parts of Finland. The location of considered areas caused several problems, the most important one is the lack of visible light during wintertime. The main research interest has been the classification of clouds from satellite images by means of neural network methods.

There have been several studies concerning the cloud detection and the classification of cloud types from a satellite image since 1970's [1] [18]. Statistical methods have been widely applied to cloud detection, for example in [3] [11] [10]. Saunders and Kriebel developed a thresholding method for detecting clear sky and cloudy radiances [19]. Karlsson and Liljas have used multispectral threshold algorithms to construct an operational classifier for cloud types, precipitation intensities, and snow extent [9]. An automatic cloud detection algorithm was developed by Derrien et al. [4]. The method is based on threshold tests applied to different combinations of channels.

Texture measures have been introduced in cloud recognition by Kittler and Pairman in 1985 [13]. They used texture measures to detect clouds from the sea and then to discriminate between cloud types. Ebert developed a method for polar cloud classification [5] [6]. Ten texture and spectral features were combined with a maximum likelihood decision rule to identify regions of various surfaces and cloud types.

Some neural network based methods have also been applied to cloud classification since the end of the 1980's. The multilayer perceptron was used by Key et al. [12], Benediktsson et al. [2], and Lee et al. [17]. The use of neural network as a classifier was promoted by Welch et al. after the evaluation of several methods [23]. The Self-Organizing Map was used by Visa et al. [22][21].

2 The Cloud Classifier

The classification of a satellite image is done in two phases (Figure 1). In the first phase the clouds are separated from the surface (referred as *cloud screening*), and in the second phase the cloudy regions are further classified into ten different cloud types (referred as *cloud classification*).

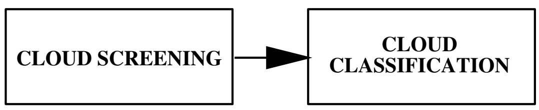

Figure 1: The classification is done in two phases.

In the cloud screening phase each image pixel is classified as open sea, land, snow, ice, or cloud. A feature vector $\mathbf{f}$ is extracted for each image pixel and compared with the cloud screening codebook. The codebook is generated by SOM. The classification result is obtained as a response from the best matching neuron. In the second phase the classification of cloudy regions to ten cloud types is accomplished in the similar way. A new feature vector $\mathbf{g}$ is extracted and the classification is done by comparing with the cloud classification codebook (Figure 2).

The feature selection is essential to the performance of a classifier. The actual features can be found among the features suggested in literature, for example in [9][19]. They are physically motivated. The features used in the cloud screening phase and in the cloud classification phase are depicted in Table 1. The selected features are spectral features and one texture feature. These features are valid for the current implementation of the classifier. In the first project there were more texture features [21]. Note, that there are different features for cloud classification at night.

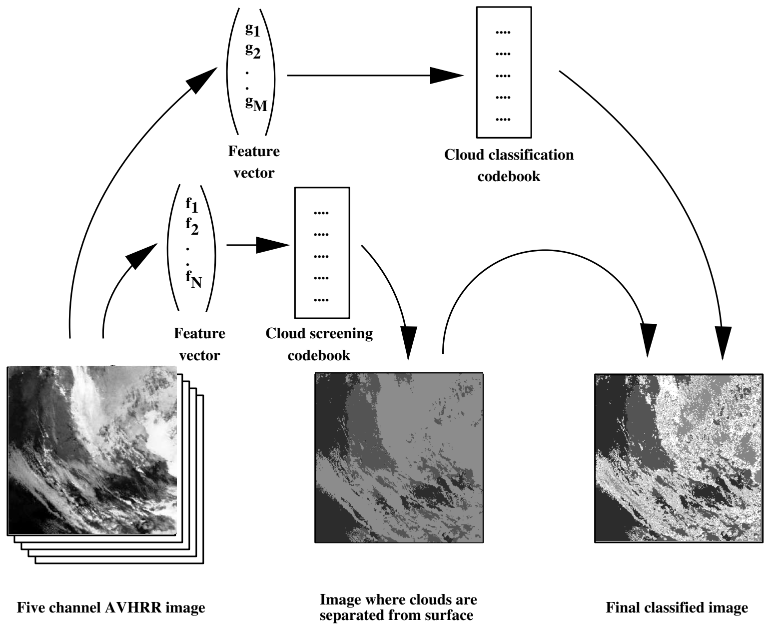

Figure 2: The classification procedure.

This is due to the absence of visible light at night. At daytime features VIS1 (0.58-0.68 μm), VIS2 (0.725-1.1 μm), and INF1-INF2 have to be normalized according to the sun zenith angle. The wavelength bands of channels INF1, INF2, and INF3 are 3.55-3.93 μm, 10.3-11.5 μm, and 11.5-12.5 μm, respectively.

	Cloud Screening		*Cloud Classification*	
Feature	*Day*	*Night*	*Day*	*Night*
VIS1			x	
VIS2	x			
VIS1-VIS2	x			
INF2	x	x	x	x
INF1-INF2	x	x	x	x
INF2-INF3			x	x
(INF1-INF2)/VIS1			x	
var(INF2)	x	x	x	x

Table 1: Features used by the classifier.

For the computational reason the codebook is splitted into several small codebooks. For each season there are four maps, making a total of 16 maps. In the training phase each sample is replaced with a feature vector. The cloud screening codebooks (a night and a day codebook) and the cloud classification codebooks (a night and a day codebook) are created in an unsupervised way with hundreds of thousands of feature vectors. First the selection of the Self-Organizing Map (SOM) [16] is strongly motivated by the fact that no preclassified samples are needed for the initial training of the network. Only a small set of known samples is needed for the labeling of the trained codebook, known also as a map. Secondly the local neighbourhood properties of the SOM are important in labeling, hence only a small set of known samples are available. The Learning Vector Quantization [14][15] is used for fine-tuning the maps.

3 Discussion

One can ask what is the reason to implement the classifier with neural networks? The main reason is that the classifier can be easily created by training. The neural network classifiers are more than traditional classifiers. The neural network classifiers have the ability to generalize, make simple models of processes or phenomena. The Self-Organising Feature Maps and the Learning Vector Quantization are suitable tools for creation of a classifier. The self-organising process works in an unsupervised way. Plenty of training samples are needed but the samples are unclassified in advance. The LVQ requires known samples, but the number of necessary samples is limited if the codebook is arranged with a SOM. The training samples should, however, be representative for the actual process or the phenomena. The neural network methods are not good in extrapolating far away outside the set of the training samples. It has been noted several times during the projects.

A suitable pre-processing of the samples and a feature selection are still necessary to improve the performance of a neural network classifier. Neural network methods can, however, be used as a tool in a feature selection. Some neural network methods are more suitable than others in a feature selection but depending on the problem, for instance SOM can be used for that purpose [8]. It can also be stated that an analytic, physical model is still superior to a neural network, but a neural network offers a rapid way to get good results and to study the process.

The computational complexity is an important point. This is something that depends on the actual implementation of the neural network method. The described approach took to execute during the first project a little less than half an hour on a Silicon Graphics Iris Indigo workstation. The 512*512 satellite image consisted of five wavelength bands. The map size was 254 elements and the length of the feature vector was fourteen. During the second project the execution time was ten minutes on the same platform and on the same image size. There were 16 maps consisting of 84 elements and the length of the feature vector was nine. The time due to the pre-procesing and the feature extraction was included into the execution time. The training of the classifying maps take several hours. Fortunately, it is sufficient to create the classifying maps only once.

The execution time should be compared with the achieved results. The results based on the described approach are not bad. For instance if the detection of the cloud cover is considered the results are equal or better than with the conventional thresholding techniques [7]. The detection of the cloud cover is relative easy to compare and to verify. The results vary in the cloud classification from very good for summer time, to good for spring time and autumn, to relatively good for winter time [7]. The main reason for this variation is the lack of illumination and it can not be helped with neural network methods.

The reported cloud classifier approach is intended to automate the processing of satellite images. The classifier is fully automatic, and it can be adapted to changing situations with new examples. The quality of the classifier has been verified with hundreds of images. The comparisons with other published results show that the performance of the classifier is relatively good. The improvement of wintertime classification is the main objective for future work.

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