40 Satellite Image Analysis

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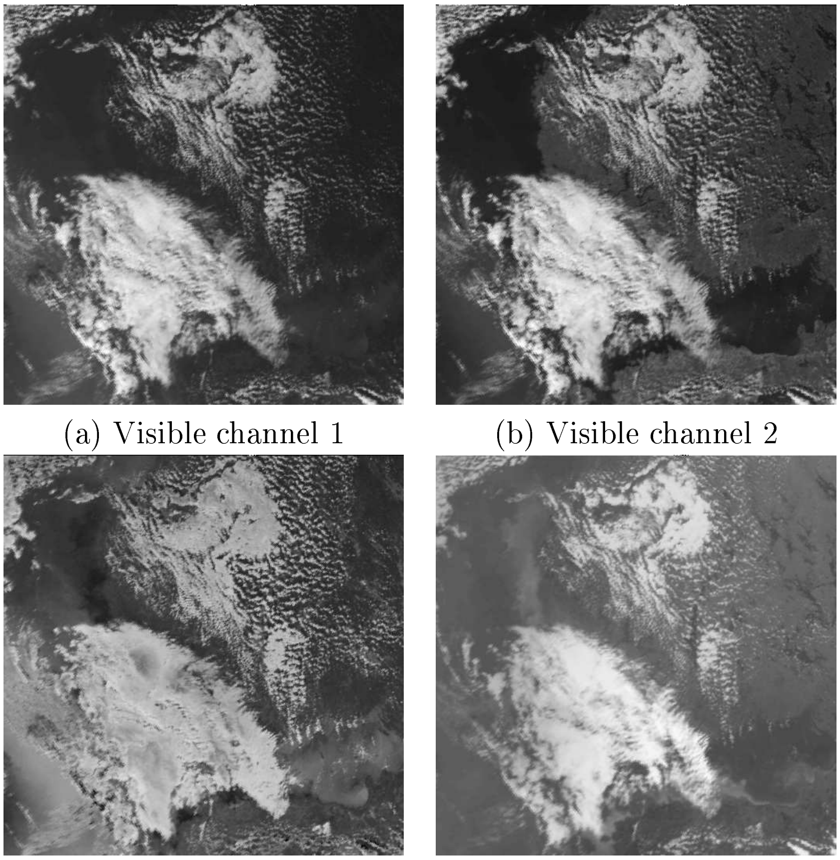
The Finnish Meteorological Institute (FMI) receives the high-resolution satellite images from weather satellites. The images are used for weather forecasting daily. The need for automatic methods to cloud detection was a main motivation for the present study. The automatic interpretation of satellite images has been studied in two projects in the Laboratory of Computer and Information Science in Helsinki University of Technology since 1991 [1-5]. 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 main interest has been the classification of clouds from satellite images by means of neural network methods.



(a) Visible channel 1 (b) Visible channel 2

(c) Near-infrared channel 3 (d) Infrared channel 4

Figure 79: AVHRR channels of the NOAA-11 satellite image. The image was taken over southern Finland on 19th September, 1993, at 12:06 p.m. (GMT).

The applied satellite images are collected by the AVHRR on board the NOAA-10, the NOAA-11 and the NOAA-12 polar orbiting satellites. The AVHRR data consist of visible, near-infrared, and infrared channels (4 or 5 channels depending on satellite) (Figure 79). In Scandinavia the low level of daylight during the winter causes severe problems to the utilization of weather satellite images.

40.1 The Cloud Classifiers

The classification of a satellite image is performed in two phases. 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*).

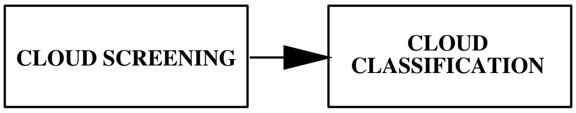


Figure 80: The classification is performed in two phases.

40.1.1 The First Classifier

The classification of clouds was based on the Self-Organizing Map (SOM) and on the Learning Vector Quantization (LVQ). A simple thresholding procedure was used in cloud screening. The selection of the Self-Organizing Map for the cloud classification in the present work was strongly motivated by the fact that no preclassified samples were needed for the initial training of the network. The feature maps were computed with hundreds of thousand unclassified feature vectors, obtained from tens of images acquired at different times of day and year. A small set of 260 preclassified samples was used only for the labeling and fine-tuning of the trained map.
The cloud classification was performed by extracting texture and spectral features from the information inside a gliding window. The window scanned all the bands of the satellite image at the same time. The extracted feature vector was fed to the classifying map. The classification result was obtained as a response from the best matching neuron. The classification result of the actual image point is the label of the best matching neuron. The procedure is shown in Figure 81.

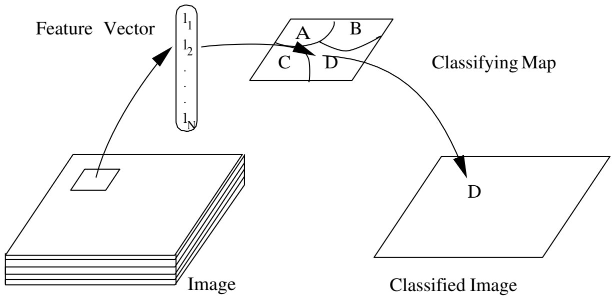


Figure 81: The cloud classification process.

40.1.2 The Second Classifier

When evaluating the first classifier there were situations where it clearly made false classifications. Because the classifier was taught with neural network methods, it was hard, sometimes impossible, to say what causes these false classifications. It is important for the finetuning of the classifier to know if the false classification is due to the classification method itself, or to something else, perhaps to a false classification of the preclassified sample.

This was the reason why a simplified classifier was used in the second approach. In the simplified classifier the codebooks are formed straight from the preclassified samples. This means that the feature vector of a preclassified sample is used as a codebook vector. The classifier consists of 32 codebooks. Each of the four seasons has four codebooks, a night and a day codebook for cloud screening and a night and a day codebook for cloud classification. The surface and cloud samples were collected by an experienced meteorologist. The samples were taken from the NOAA-11 satellite images between autumn 1991 and autumn 1993. The total number of samples is 1106.
In the cloud screening procedure a feature vector is extracted for each image pixel and compared with the codebook. The label of the best-matching codebook vector is presented as output. The classification of cloudy regions is then accomplished. A new feature vector is extracted and the classification is done as in the cloud screening procedure (Figure 82). The pooled form KNN algorithm ($K = 3$) with the Hamming distance is used to find the correct classifications in both procedures.

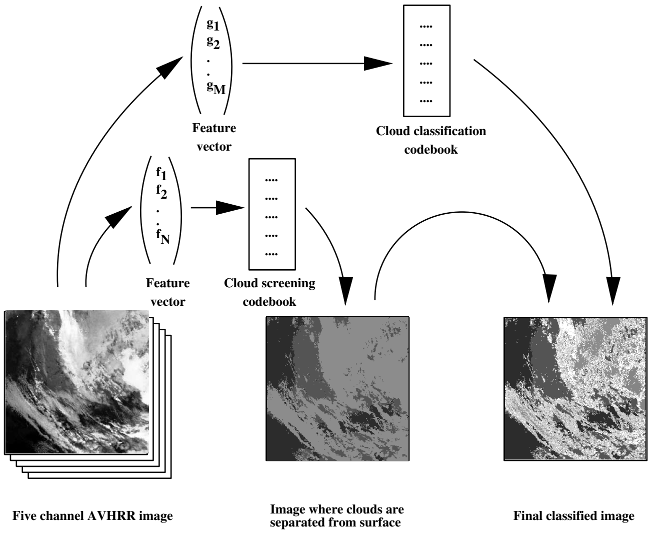
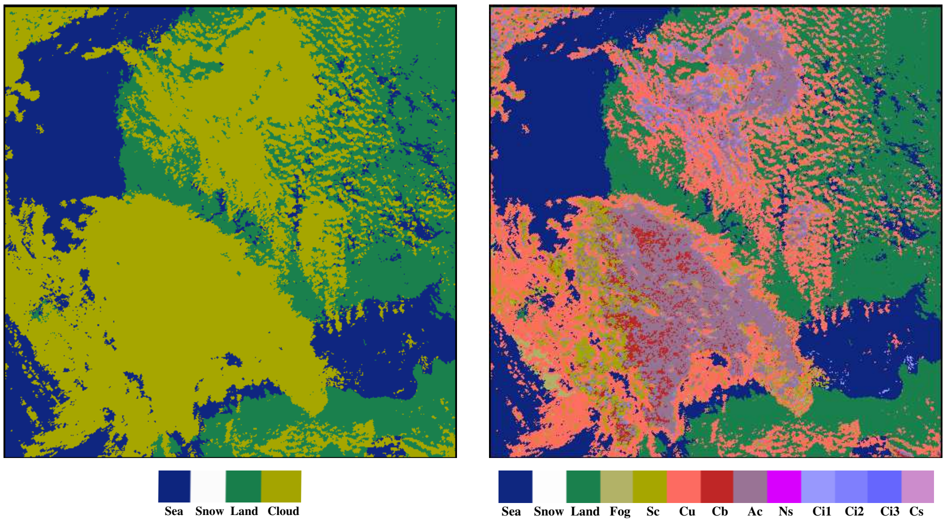


Figure 82: The classification procedure. Only cloudy regions are considered in cloud classification phase.

The classes used in cloud screening procedure were open sea, land, and cloud. In wintertime snow and ice were also classified (Figure 83(a)). The cloudy areas were further classified to ten cloud types which were cirrus over land/sea (Ci1), cirrus over low clouds (Ci2), cirrus over middle clouds (Ci3), cirrostratus (Cs), altostratus/altocumulus (Ac), stratus/stratocumulus (Sc), fog/stratus (Fog), cumulus (Cu), cumulonimbus (Cb), and nimbostratus (Ns) (Figure 83(b)).

40.2 Conclusions

Two versions of multispectral cloud classifiers were implemented to automate the processing of satellite images. The classifiers are automatic, and they can be adapted to changing situations by giving new examples. In the first approach the training of the classifier was done with the SOM and the LVQ algorithms. Neural networks offer a rapid way to get good results and to study the process. The use of neural



(a) Cloud screened image (b) Final classification

Figure 83: Classifications of the NOAA satellite image in Figure 1. In (a) is the classified image after cloud screening procedure, and in (b) is the final classification.

networks during the development process made it possible to reach the present stage in four years. However, in the final evaluation study a simplified classifier was used so that the false classifications could be traced and possible corrected.
The quality of the classifier has been verified with hundreds of images. In addition to the visual inspection, the automatic evaluation scheme is developed [1,3]. The comparisons with other published results show that the simplified classifier is working relatively well. The cloud classifier is in the evaluation use at the Finnish Meteorological Institute.

References

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