Experiences from operational cloud classifier based on Self-Organising Map

Ari Visa, Kimmo Valkealahti, Jukka Iivarinen, Olli Simula
Helsinki University of Technology
Laboratory of Information and Computer Science
Rakentajanaukio 2 C, FIN-02150 Espoo
Finland

Abstract

A new operational system to interpret satellite images is represented. The described method is adaptive. It is trained by examples. In the reported application a combination of textural and spectral measures is used as a feature vector. The adaptation or learning of the extracted feature vectors occurs by a self-organising process. As a result a topological feature map is generated. The map is identified by known samples, examples of clouds. The map is used later on as a code book for cloud classification. The obtained verification results are good. The represented method is general in the sense that by reselecting features it can be applied to new problems.

1 INTRODUCTION

For weather forecasts fast, reliable, and covering observations are needed. An observation network is an expensive way to gather a synoptic view of weather. Weather satellites offer a proper tool for the data acquisition. They can provide information of temperature, cloud cover, type, and organisation, wind speed and direction, and so on. The data interpretation, however, is not a straightforward procedure. Visual cloud classification is a tedious and time consuming task. The interpretation depends highly on the expertise of the observer. A typical weather satellite image consisting of five wavelength bands is illustrated in Figure 1.

US National Oceanic and Atmosphere Administration (NOAA) provides a series of polar-orbiting satellites carrying visible and infrared radiation radiometers. The NOAA satellites are sun-synchronous which means that their orbital plane is fixed in relation to the sun. The illumination conditions of the images covering a specific area can be considered almost constant from day to day. The orbital time of a NOAA satellite is 102 minutes. The images are produced by a Advanced Very High Resolution Radiometer (AVHRR), a rotating mirror that scans the view perpendicular to the orbit. Each scan line covers approximately 2800 kilometres and consists of 2048 10-bit grey scale values. The AVHRR instrument of the satellite gives multispectral data in five wavelength bands.

The classification of clouds from a weather satellite image is not a new problem. It has been studied since 1970s [1]. Several methods exist for cloud detection and classification from visible and infrared satellite measured radiances. Statistical classification procedures have been applied widely [3, 7, 13, 15]. A threshold algorithm for classifying four types of clouds over the tropical ocean has been studied by Inoue [11]. Two infrared AVHRR channels have also been used in his study. Texture measures have been introduced in the middle of 1980s to cloud recognition by Kittler [16]. A texture measure has been

Figure 1: *A NOAA weather satellite image consisting of five wavelenght bands as they are shown on a screen. The image is of Nordic countries.*

used first to discriminate between clouds and sea surface and then to discriminate between cloud types. Ebert has combined texture measures and a maximum likelihood decision rule to indentify regions of various surfaces and cloud types at high latitudes [4, 5]. In her study eight spectral and textural features have been extracted from AVHRR data for $32 * 32$ pixel regions (corresponding to areas of $96 * 160$ km size). Multispectral threshold algorithms have been developed by Karlsson and Liljas [12]. Their goal has been to construct an operational classifier for cloud types, precipitation intensities and snow extent. They have utilized all five channels of the NOAA AVHRR instrument and textural information from one infrared channel. The classification has been matched to different seasons of the year, to sun elevation, and to satellite. The classifier is in operational use but the number of thresholds needed in this method is very high, some thousands.

Recently, some neural network based methods have been suggested [14, 21, 25, 26]. Key et al. have used a backpropagation network. They have reported that a neural network approach offers advantages in easy use, interpretability, and utility for indistinct and time-variant spectral classes. Smottroff et al. have used artificial neural networks as trainable classifiers. They have reported also good classification results [21]. Visa et al. have used a self-organising process to cluster feature vectors to a topological feature map. Known samples have been located on that map and the labeled map, called the classifying map, has been used to interpret cloud pictures. Welch et al. [26] have tested several neural network methods on six AVHRR images. They have promoted the use of a neural network as a classifier.

1.1 Problem formulation

The purpose of the reported research work has been to develop an operational system that classifies clouds from NOAA weather satellite images continuously from day to day and from year to year. The clouds are classified into nine classes. Land, open sea, ice or snow, and sunglints are of limited interest in meteorology but they are indicated in images. There are altogether nine pure cloud types as Cirrus, Cirrostratus, Altostratus, Altocumulus, Stratus, Stratocumulus, Cumulus, Cumulonimbus, and Nimbostratus. In addition, it is possible that there are up to three layers of clouds on each other at the same time. At most nine classes are used to represent mixtures of cloud types. These extremely difficult cases are only shortly indicated in this paper.

An extra difficulty is introduced by the northern location of the interesting region. The illumination conditions are complicated due to low illumination angles. Finland is situated between 60th and 70th latitude in north. This means that the interesting area is mostly in darkness during the winter. The visible wavelength bands are not useful. In the morning and in the evening the low illumination angle makes the clouds look quite different from the appearance at midday. All these problems have been understood and expected. There are also some other expected problems. The discrimination between snow and ice, and clouds is complicated due to the actual wavelength bands. It is also difficult to make a reliable discrimination between a thin stratus cloud and a land surface.

The problem is formulated in the first section of the paper. The consideration of the problem differs from the most of published papers. The second section describes the developed method. In section three some experiences of the developed method are discussed. The results are projected back to the problem formulation. The evaluation results from the Finnish Meteorological Institute are indicated. The results are based on the period between the autumn 1991 and the autumn 1993.

Band	*Wavelength [μm]*	*Interpretation*
VIS1	0.58 - 0.68	Visible
VIS2	0.725 - 1.1	Visible and Near-infrared
INF1	3.55 - 3.93	Near-infrared
INF2	10.3-11.5	Infrared
INF3	11.5 - 12.5	Infrared

Table 1: *The actual wavelenght ranges of NOAA-11 and NOAA-12 AVHRR images. The band INF3 is not available from NOAA-12 satellite.*

2 Developed system

The cloud classification is performed in two steps. First, the clouds are screened and then they are classified. Clouds are separated from surface before the texture and spectral features are calculated, since the applied features are not adequate to discriminate low clouds from surface at low illumination angles. The whole system is illustrated in Figure 2. A texture descriptor is calculated for each cloud pixel from one infrared band. This description and some spectral measures are fed to the map which gives the best matching prototype and the classification. The feature map is created by means of neural computation.

Figure 2: *The described system consists of three modules.*

2.1 Image acquisition

The applied satellite imagery is collected by the AVHRR instrument on board the NOAA-11 and NOAA-12 polar orbiting satellites. Data consists of visible, near-infrared, and infrared radiances. The actual wavelength ranges are given in Table 1. The data from INF3 of is not always available in the classification, since NOAA-12 does not have an instrument for that wavelength band. The AVHRR images are received by the Finnish Meteorological Institute. The scene covers the whole Scandinavia with the resolution 1.1-by-1.1 kilometres in the centre of the scan line.
The received raw data is geometrically transformed and mapped approximately to the same chart position. Final images are 512-by-512 pixels in size with 4 kilometre resolution. Original 10-bit pixel values are reduced to 8 bits providing 0.5 K resolution in the thermal channels.

2.2 Pre-processing

Hence the illumination angle, α, varies the acquired images have to be normalised due to illumination, see Figure 3. This is a necessity to the visible bands and the near-infrared band. The normalisation is naturally done during daytime, when the sun elevation is more than zero degrees. The cloud screening is based either on the VIS1 or on the difference of the INF1 and the INF2. These values are compared with empirical thresholds. The VIS1 is used over the sea and the difference is used over the land, hence the band VIS1 is not capable to discriminate between snow and clouds. The difference of thermal bands is less sensitive to snow. The near-infrared band, INF1, is also normalised. The difference of the

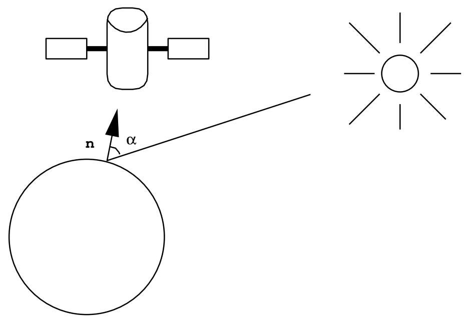


Figure 3: *An illustration of the illuminance conditions*

Spectral Feature	*Day*	*Night*
INF2	x	x
VIS1 (normalised)	x	
INF1 - INF2 (normalised)	x	
INF1 - INF2		x
INF2 - INF3	x	x
(INF1 - INF2)/VIS1	x	

Table 2: *The spectral information from different bands are used. The selected spectral features are given in table.*

bands INF1 and INF2 approximates the albedo of the INF1. During night another procedure to cloud screening is applied [6]. The method is, however, slightly modified. The clustering is accomplished by a small Self-Organising Map. Which of the two described discrimination methods is used depends solely on the illumination angle at the actual pixel. One should observe that both approaches may be used in the same image depending on the location of the day-night-border.

2.3 Selected features

There is a great acceptance that both spectral and texture features are needed in cloud classification [8]. The selected spectral features are given in Table 2. In addition to the given spectral features textural features are also used. Because the weather satellite images consist of almost stochastic textures, the co-occurrence matrices [9] have been selected for the texture description. The co-occurrence matrix method has been found to be good to classify stochastic textures [27, 2]. The co-occurrence matrix $M_d(i,j)$ is a second order statistical measure of grey level variation. The disadvantage of the co-occurrence matrix method is that it discards the shape information in an image, which is not a drawback, when stochastic textures are considered.

For time and space complexity reasons, each co-occurrence matrix $M_d(i,j)$ is replaced by the three measures; energy (1), inertia (2), and entropy (3). The measures of each matrix are normalised [24].

$$Energy = \sum_{i}^{G} \sum_{j}^{G} M_d(i,j)^2 \tag{1}$$

$$Inertia = \sum_{i}^{G} \sum_{j}^{G} (i-j)^2 M_d(i,j) \tag{2}$$

$$Entropy = -\sum_{i}^{G} \sum_{j}^{G} M_d(i,j) log M_d(i,j). \tag{3}$$

The problem concerning improper spatial resolution is alleviated by using a set of different displacements. The final feature vector is formed by concatenating the measures of each matrix. The different steps in the feature vector construction are depicted in Figure 4. The feature vector is calculated locally within a small window that glides across the image. The window size is also a compromise. The size of the window should be small that the lowpass filtering effect due to masking remains tolerable, but it should also be large enough so that the extracted information has statistical significance.

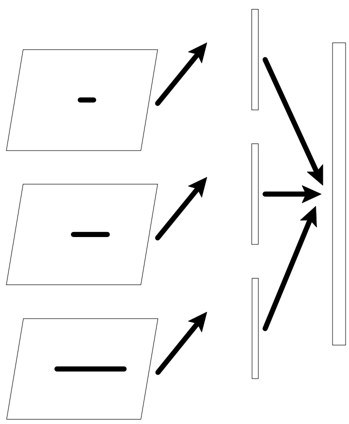


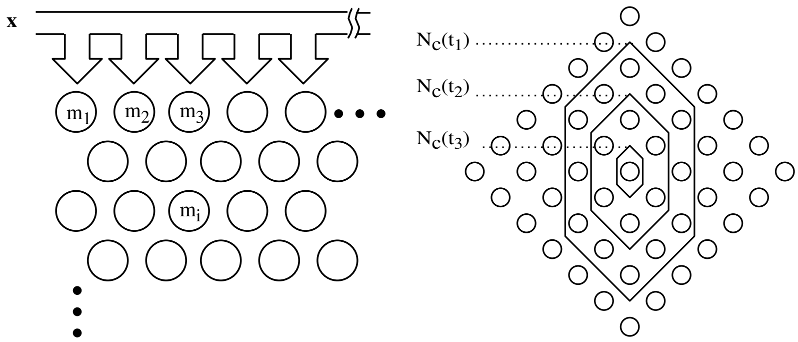
Figure 4: *The texture measures are used in multiresolution sense.In the first step, the co-occurrence matrices are gathered. In the second step, a co-occurrence matrix is replaced by three measures. The final feature vector is formed by concatenating the measures of each matrix.*

2.4 Classification

The classification of clouds is based on the Self-Organising Map (SOM) and on the Learning Vector Quantisation (LVQ). The map is a spatially organised representation of the possible feature vector space. The presentation is created by means of neural computation [20]. The elements of the feature map become tuned to clusters of feature vectors through an unsupervised learning process. The learning is accomplished by giving the SOM a large amount of feature vectors. The number of classes can be unknown in advance.

The feature map consists of a set of neurons that are topologically arranged with a two-dimensional coordinate system, see Figure 5(a). The grid structure is arranged in a hexagonal form, where each neuron can be thought to have a direct symmetric neighbourhood with six neurons. The neighbourhood includes all elements within a certain distance from the central neuron. In Figure 5(b), some neighbourhoods of different sizes are presented.

When a feature vector $\mathbf{x} = [x_1, x_2, \cdots, x_n]^T$ is the input to the map, the best matching neuron with a weight vector $\mathbf{m}_c = [m_{c1}, m_{c2}, \cdots, m_{cn}]^T$ is the output. The match is measured by the Euclidian



(a) Element arrangement (b) Neighbourhoods

Figure 5: *In Figure (a), the element arrangement for the feature map is presented. In Figure (b), examples of topological neighbourhood N_c are presented. The learning stage is defined by t, $t_1 < t_2 < t_3$.*

distance between the vectors $\mathbf{x}$ and $\mathbf{m}_i$. The learning process involves updating of the best matching neuron $\mathbf{m}_c$ of the map and those neurons located in the neighbourhood N_c around it. At the initial stage, the neurons usually contain random weight vectors. At each learning step, a new input vector $\mathbf{x}$ is fed and the best matching neuron for the input vector is calculated.

$$\|\mathbf{x} - \mathbf{m}_c\| = \min_i \{\|\mathbf{x} - \mathbf{m}_i\|\} \tag{4}$$

The updating of the weight vectors at each step includes the neighbourhood $N_c(t)$, others remain untouched:

$$\mathbf{m}_i(t+1) = \begin{cases} \mathbf{m}_i(t) + \alpha(t)[\mathbf{x}(t) - \mathbf{m}_i(t)] & \text{if } i \in N_c(t) \\ \mathbf{m}_i(t) & \text{if } i \notin N_c(t) \end{cases} \tag{5}$$

The neighbourhood $N_c(t)$ is usually dependent on time t, $0 < t \leq$ total sample count. Initially, the neighbourhood N_c is quite wide but during the learning it shrinks until $N_c = \{\mathbf{m}_c\}$. The learning rate $\alpha(t)$ is a monotonically decreasing function, $0 < \alpha(t) < 1$, which determines the speed of learning.

The learning samples are randomly taken from the satellite images during the learning process. Because the feature vectors are extracted from these samples the feature vectors may represent mixtured cloud classes. This can be observed during the labeling.

The labeling of the SOM neurons $\mathbf{m}_i$ is done in a supervised way according to known samples. This process is illustrated in Figure 6. A limited number of known samples are sent to the map, and the best matching neuron is activated by each input. Most of the neurons get the labeling through the majority voting. The neurons that have responded only to a certain class get the label of the class. It is also possible that the neuron has got no label or the neuron has responded to samples of several classes. In the latter case a fine tuning is needed. Determining the appropriate class in labeling can be difficult, the since number of the known samples for a certain class may vary in practice.

After the labeling the classifying map may have still some ambiguous neurons. This problem is alleviated by a supervised learning technique, Learning Vector Quantization [17, 18, 19]. The LVQ is given by the formula (7). Assume that $\mathbf{m}_c$ is the neuron that is closest to a feature vector $\mathbf{x}$. Let $\mathbf{m}_c$ belong to class

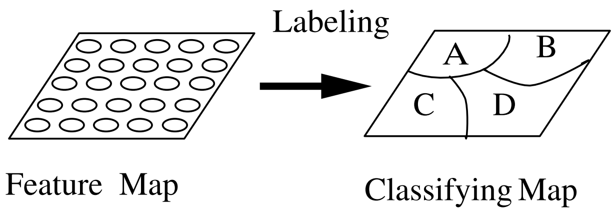


Figure 6: *The topological feature map is labeled by known samples.*

C_s. The correct classification of $\mathbf{x}$ is C_r. The fine tuning works in two phases: First the best matching neuron $\mathbf{m}_c$ is found, then the updating is done in the following way:

$$\begin{aligned} \mathbf{m}_c(t+1) &= \mathbf{m}_c(t) + \alpha(t)(X(t) - \mathbf{m}_c(t)), \text{ if } C_s = C_r \\ \mathbf{m}_c(t+1) &= \mathbf{m}_c(t) - \alpha(t)(X(t) - \mathbf{m}_c(t)), \text{ if } C_s \neq C_r \\ \mathbf{m}_i(t+1) &= \mathbf{m}_i(t) \text{ ,if } i \neq c \end{aligned} \tag{6}$$

where $\alpha(t)$ is a decreasing function of time.

The operational cloud classification is performed by extracting texture and spectral features from the information inside a gliding window. The window scans all the bands of the satellite image at the same time. The extracted feature vector is fed to the classifying map. The classification result is 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 7.

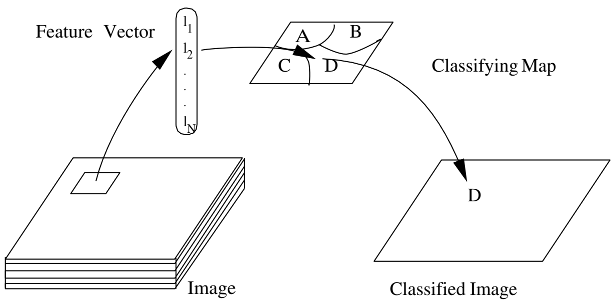


Figure 7: *The cloud classification process.*

3 EXPERIENCES AND DISCUSSION

The verification of the system behaviour is a difficult task. The main difficulty is the lack of suitable reference material. The reports from weather ground stations, tell only the cloud type but neglect the shape and size information. Weather radars give information about the shape and location of rain clouds. This information is useful but it is available only for rain clouds in certain parts of Finland.

The evaluation of the system is split into three categories. The first category, the evaluation of daytime images is ready. The results are reported here. The two other gategories, the evaluation of night images and the evaluation of low illumination angle images, are still under work. Preliminary results on the performance of the developed system have also been presented in [23]. To evaluate the system

Layer	*Cloud Generus*	*Abbreviation*	*Number of Samples*
High Clouds	Cirrus over sea/land	Ci	26
High Clouds	Cirrus over low clouds	Ci	18
	Thick Cirrostratus	Cs	30
Middle Clouds	Altostratus/Altocumulus	As/Ac	29
Low Clouds	Stratus/Stratocumulus	St/Sc	25
Thick Clouds	Cumulus	Cu	19
	Cumulonimbus	Cb	41
	Nimbostratus	Ns	30

Table 3: *Information of the available preclassified cloud samples*

Cloud Generus	*Number of Training Samples*	*Classification Ratio [%]*	*Number of Test Samples*	*Classification Ratio [%]*
Cirrus over sea/land	13	100.0	13	92.3
Cirrus over low clouds	9	100.0	9	88.9
Thick Cirrostratus	15	73.3	15	26.7
Altostratus/Altocumulus	14	92.3	15	73.3
Stratus/Stratocumulus	12	91.7	13	92.3
Cumulus	9	100.0	10	80.0
Cumulonimbus	20	95.0	21	90.5
Nimbostratus	15	100.0	15	93.3
Total	107	93.5	111	79.3

Table 4: *The classification results based on available preclassified cloud samples. The classification rates are given to both training and testing samples*

performance on daytime images 221 preclassified samples were collected during summer. The samples were selected by choosing small, well-defined regions containing only one cloud type. 43 satellite images were used. The selection was done by experienced meteorologists from the Finnish Meteorological Institute. The tested cloud types, the abbreviations, and number of available samples are given in Table 3.

The size of the classifying map is eleven by fourteen. The tested map was intended for summer time. The amount of data during the unsupervised learning was 260000 samples, the initial learning rate was 0.6 and the radius 10. The fine tuning and the labeling were based on 107 preclassified samples. The data set was split into two separate groups, one learning set and one test set. During the classification the feature vector consisted of fourteen features, nine textural and five spectral features. All the fourteen features are used for daytime samples. During the night the length of the feature vector is only twelve, this means nine textural and three spectral features. The preliminary test results are given in Table 4, note that all the test samples are daytime ones. It can be observed that Nimbostratus (Ns) is classified 93 per cent correctly and Stratocumulus/Stratus (Sc/St) 92 per cent correctly. The most problematic cloud type is thick Cirrostratus (Cs). It resembles other cold, thick clouds. The overall classification rate 79.3 per cent can be considered as a good result to an operational system.

The developed method, however, is not totally free from problems. Some expected practical problems have occured during the evaluation. For instance, the separation between snow and clouds do not work perfectly. The same situation is with clouds and sun glints. There are also some problems to separate clouds from the background during the night. This is difficult when there exist some inversion layers. The temperature inversion is a layer of atmosphere in which the temperature increases with altitude as opposed to the normal tendency for temperature to decrease with altitude. This situation occurs time by time during the winter. These problems are mainly due to limited amount of information in the available channels. In some cases the clouds are layered. The problem is that the weather stations and satellites consider and classify different layers. This is one reason to misinterpretations.

One can ask what is the reason to implement the classifier with neural networks. The main reason is that a classifier can be easily created by training. The neural network classifiers are more than traditional classifiers. The neural network classifiers have the ability to generalise, make simple models of processes or phenomenena. The Self-Organising Feature Maps and the Learning Vector Quantization are, especially, 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. However, the training samples should be representative for the actual process or the phenomen. The neural network methods are not good to extrapolate far away outside the set of the training samples. It has been noted several times during the project. A suitable pre-processing of the samples and a feature selection are still efficient methods to improve the performance of a neural network. 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.

As a whole, it can be stated that the method has so far worked as expected at the begining. It is, however, too early to state any other classification rates than those mentioned for the day time. Two years of evaluation is a short time to verify the whole behaviour of the system. The verification of the system during night time and at low illumination angles is still going on. The verification is obtained by comparing the automatic classification results with manually preclassified images. The preclassification is done by experienced metheorologists and their results are considered reliable. In our verification the result is considered to be correct only if it is equal to the preclassified result. However, the experienced metheorologists may make mistakes, too. In addition, the classification rates are pessimistic due to shape inaccuracies of the clouds. The scanning window acts also as a filtering mask, which may cause narrow contours between different textures, and in general, smooth border lines around clouds.

The computational complexity is also an important point. It takes less than half an hour to process an ordinary 512*512 satellite image consisting of five wavelength bands. This processing is done on a Silicon Graphics Iris Indigo workstation. The processing time varies a little depending on data. The feature extraction from images and the training of the classifying map take several hours. Fortunately, it is sufficient to create a classifying map only once.

4 ACKNOWLEDGEMENTS

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