# Self-Organizing Feature Maps in Texture Classification and Segmentation

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**Abstract**

Textures and self-organizing feature maps have recently been shown to be applicable in many areas of image analysis. In this paper, some texture-based classification and segmentation examples are described.

## 1 Introduction

Vision systems are often considered to be composed of two sub-systems, referred to as early vision and cognition, or low-level and high-level vision. Low-level vision consists mainly on image processing. The input image is transformed to another image, with more favourable characteristics. The high-level vision processes include object recognition and scene interpretation. Segmentation, the grouping of parts of an image into regions that are homogeneous with respect to one or more characteristics, serves as a bridge between low-level and high-level vision processes.

Texture, a term that is difficult to define formally, may be viewed as a descriptor for providing a measure of image properties, such as e.g. smoothness, coarseness, and regularity. Textures can be grouped into deterministic, stochastic, and real ones. Textures, or differences between textures, are used as a part of human decision making. Thus, texture is one of the features that might be used for grouping. It might also be the object to be recognized.

In many practical applications of image processing and analysis texture plays an important role. Some of the most important areas are classification, image segmentation, image coding, and computer graphics. The classification of textures is common in medical image processing and process control. Some typical applications are the recognition of tissues in microscope images, the quality control of timber, line boards and paper, or the classification of reconnaissance and remote sensing images. Image segmentation is related to the classification problem. One criteria of image segmentation might be texture. This assumption is valid when other features, like shapes, tones or colours, are not sufficient to discriminate between regions.

The greatest problem with the classical pattern recognition process is the need of a considerable amount of known samples. In the case of textures, the collection of known samples is especially expensive and tedious. The training has traditionally been done in a supervised way in which the operator gives known samples to the classifier. Neural network methods, especially the self-organizing process, offer suitable tools to overcome the tedious and expensive training process. The training can be accomplished in an unsupervised way and the classified samples are needed only in fine-tuning the prototypes. One additional advantage of neural network methods is that continuos learning during operation is possible allowing adaptation to changing situations.

# 2 Self-Organizing Feature Map in Pattern Recognition

The classical pattern recognition process is illustrated in Figure 1. This is still a valid paradigm eventhough some parts of it are possibly implemented by neural networks. Traditionally a pattern vector is replaced with a more convenient feature vector. The feature vector is less memory demanding and contains almost the same information as the original pattern vector. There is no covering theory concerning the feature selection but there are methods to check the quality of the selected features and to reduce the dimension of the selected feature vectors [The89, Sin92]. However, some attempts to automize the feature selection have been done [Vis92a, Vis92b]. These attempts are based on one-dimensional topological feature maps.

Texture can be interpretated as a pattern but a complicated one. The feature vectors desribing texture are either reduced transformations of the original texture or estimated parameters of a texture model.

The feature vectors have been traditionally clustered by some clustering algorithms. Nowadays, this can be done by several neural network methods. For example a self-organizing process [Koh89] is a proper tool for that. The feature vector $X$ is inputted to a neural network consisting of $M$ neurons. The localization of the best matching neuron $m_c$ is done in following way:

$$||X - m_c|| = min_k||X - m_k||,\ k \in 0..M. \tag{1}$$

The best matching neuron $m_c$ is then adapted to $X$

$$\begin{aligned} m_k(t+1) &= m_k(t) + \alpha(t) * [X - m_k(t)], \text{ for k} \in N_c \\ m_k(t+1) &= m_k(t), \text{ for } k \neq N_c. \end{aligned} \tag{2}$$

It is important that the function $\alpha(t)$ and the neighbourhood $N_c$ decrease with respect of time. These factors take care of estimation of density and topology. A large number of feature vectors $X$ is naturally needed but this training is totally done in unsupervised

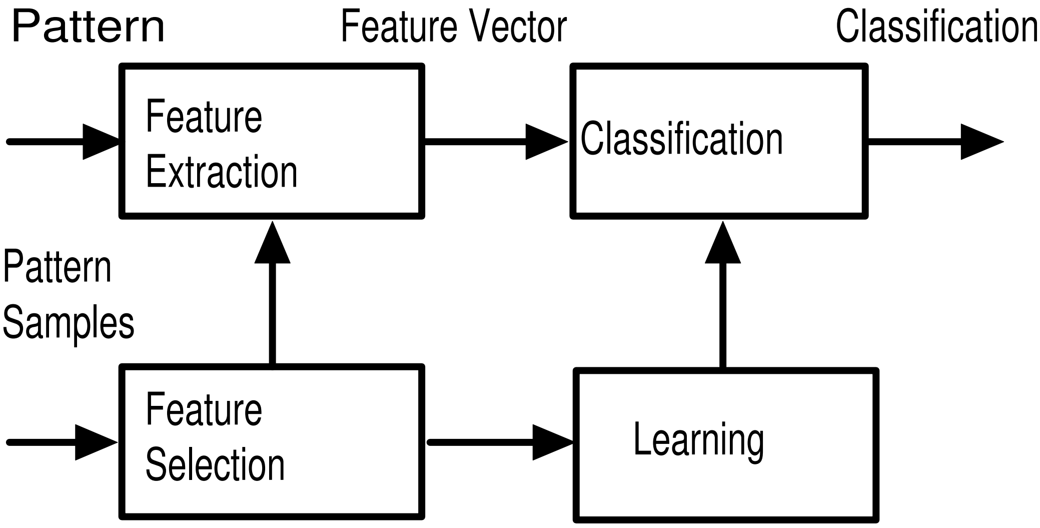


Figure 1: Block diagram of a decision-theoretic pattern recognition system by Fu and Rosenfeld.

way. The result is a topological feature map.

The topological feature map has some important properties. These properties are independent of the shape of the map. The dimension of the map might be one, two or higher but the one and two-dimensional maps are easy to visualize and are hence preferable. Firstly, adjacent neurons on the map are similar. This is an important property when one considers a classification error. Secondly, a $m_c$ or several $m_c$:s estimate posterior probability density function of feature vectors. These are important properties considering a pattern recognition or an image segmentation problem.

# 3 Applications

The adaptive method based on neural computation for classification and segmentation of stochastic textures has been developed by Visa [Vis90]. In remote sensing, the texture based segmentation and neural computation have been applied in satellite images and areal photographs. The method has also been used in industrial quality control applications in timber and in paper industry.

## 3.1 Cloud Classification

The classification of clouds for better weather forecasting and cloud climatology research is an important application in meteorology. Clouds have been classified from satellite images based on partly texture information [Kitt85] and grey level thresholding [Karl90]. Because clouds form stochastic textures in satellite imagery the method proposed by Visa [Vis90] is also applicable to cloud classification. In this method, the texture features are selected in such a way that the principal part of classification is based on textures. The satellite images consist of five channels, three visible and two infrared. For each channel

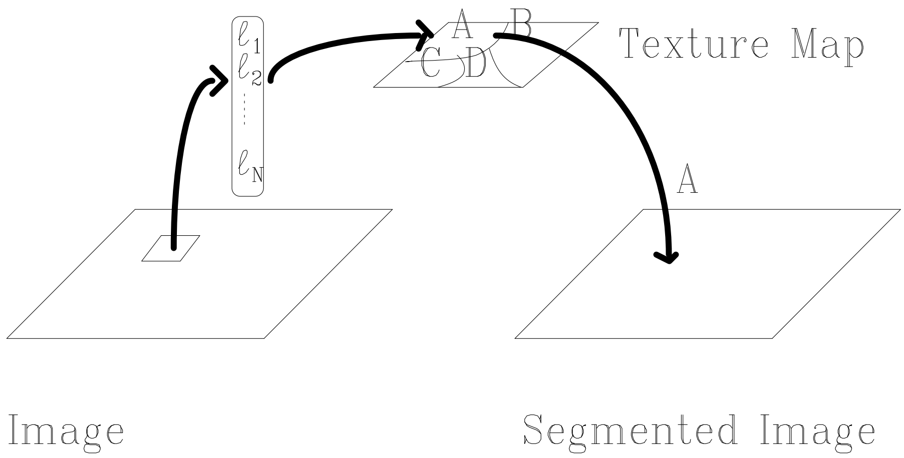


Figure 2: The segmentation method based on the texture map

the texture information is extracted using the co-occurence matrices. They are a kind of normalized histograms representing the probability that two grey level values occur at certain position to each other [Vis91].
The segmentation method is illustrated in Figure 2. A window scans over the whole image from left to right and from top to bottom. For each pixel, the co-occurence matrix is calculated for three different distances within the window centered at the pixel. The original 256x256 co-occurence matrices calculated for one pixel are reduced to 16x16 matrices and concatenated to form a feature vector. This feature vector is then compared to the earlier created topological feature map, the texture map. The comparison is done on the nearest neighbour basis. As a result, the vector element on the map mostly resembling the extracted feature vector is found. Because the texture map is labelled, i.e. each element has an interpretation defining the physical meaning (low or high cloud etc.), the classification of each pixel can be done. This classification is then transferred to the corresponding image point resulting in the segmented image. The final segmentation of the multichannel image is obtained by combining the segmented images of each channel.

As an example, channel 4 (IR) over Scandinavia taken by NOAA-11 satellite is shown in Figure 3. In the classified image, some of the cloud types as well as land and sea can be clearly detected. A prototype system for classifying clouds has been in operation since September 1991 at the Finnish Metheorological Institute.

## 3.2 Timber Classification

It is important for saw-mills to utilize the raw-material optimally. The timber is sawn and graded in many stages. In each stage the quality of the board is checked by visual inspection usually done by a human operator. Recently, some semiautomatic solutions have been suggested. In this case the surface of the board is considered as a texture. Some texture measures, similar to characterization of paper formation [Vis90], are extracted. These measures are concatenated into a feature vector that is sent to a self-organizing neural network. A topological feature map is created in unsupervised way and it is used as a set of prototypes during the grading process. The first installation at a saw-mill has

Figure 3: Original image (above left), final classified result (above right), and reference map of Scandinavia (below)

Figure 4: Some examples of board grades

been in operation since September 1991.

## 3.3 Paper Classification

At paper-mills it is essential that the paper formation, the fiber distribution in a paper, can be kept within a desired range. An impression of some different formation types is given in Figure 5. Formation images can be considered as stochastic textures. The characterization of stochastic textures has traditionally been done by co-occurrence matrices. The co-occurrence matrix is usually reduced by some features, for example energy, inertia and entropy [Har73]. In this case the co-occurrence matrices have been calculated at six distances. Each matrix has been reduced to three features, energy, inertia, and entropy [Vis90]. The features of six matrices are concatenated together to form a feature vector. This vector is inputted to a self-organizing process which creates a topological feature map. This feature map is identified and used as a code-book during the classification. The described system has been in operational use for more than three years in a Finnish paper mill.

## 3.4 Other Applications

The cloud classification method described above seems to be suitable for areal photographs as well. Preliminary tests for monitoring the amount of trees in a forest surveying application have succesfully been done. The method could be easily applied to other applications based on areal photographs, too.

Figure 5: Some examples of paper formation

## References


[Bro68] Brodatz, P., Textures: A Photographic Album for Artists and Designers, Reinhold, New York 1968.

[Har73] Haralick, R., Shanmugam, K., Dinstein, I., Textual Features for Image Classification, IEEE Trans. on System, Man, and Cybernetics, Vol. SMC-3, No.6, November, pp. 610-621, 1973.

[Karl90] Karlsson, K.-G., Liljas, E., The SMHI Model for Cloud and Percipation Analysis from Multispectral AVHRR Data, SMHI Promis Reports, August, 1990.

[Kitt85] Kittler, J., Pairman, D., Contextual Pattern Recognition Applied to Cloud Detection and Identification, IEEE Transactions on Geoscience and Remote Sensing, Vol. GE-23, November, pp. 855-863, 1985.

[Koh89] Kohonen, T., Self-Organization and Associative Memory, 3rd Edition, Springer-Verlag, Berlin, 1989.

[Sin92] Sing-Tze, B., Pattern Recognition and Image Preprocessing, Marcel Dekker Incorporation, New York, 1992.

[The89] Therrien, C.W., Decision, Estimation and Classification, John Wiley & Sons, New York, 1989.

[Vis90] Visa, A., Texture Classification and Segmentation Based on Neural Network Methods, Dissertation at Helsinki University of Technology, Faculty of Information Technology, Espoo, 1990.

[Vis91] Visa, A., Valkealahti, K., Simula, O., Cloud Detection Based on Texture Segmentation by Neural Network Methods, Proc. of International Joint Conference on Neural Networks, Singapore, November 18-21, pp. 1001-1006, 1991.

[Vis92a] Visa, A., Topological Feature Map and Automatic Feature Selection, Proc. of SPIE Science of Artificial Neural Network , Orlando, Florida, April 20-24, 1992.

[Vis92b] Visa, A., Automatic Feature Selection by Self-Organization, Proc. of The International Conference on Artificial Neural Networks, Brighton, UK , September 4-7, 1992.