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mixed pixels, desert varnish etc. Figure 4 shows two minerals, which have been misclassified as gipsum.

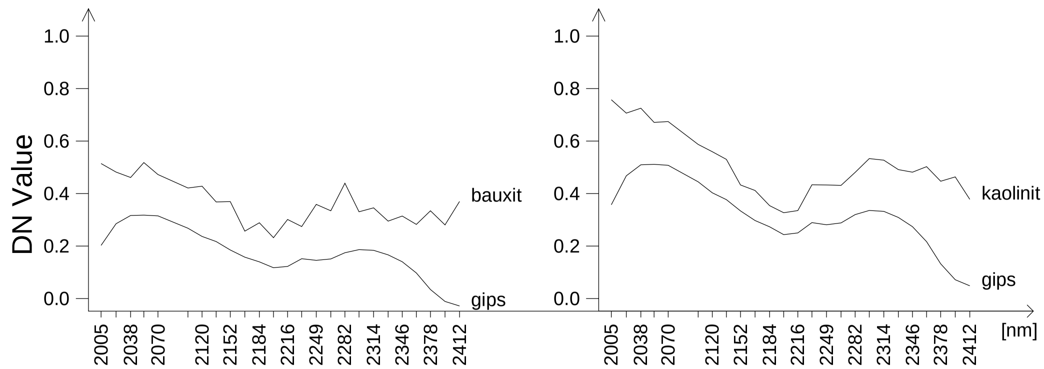

Figure 4: Misclassified samples.

The first sample (bauxite) shows the influence of the insufficient SNR of the GER sensor within the SWIR range, that eliminates the characteristic feature combination of this strata composed of Fe-constituents and kaolinite. Mixed pixels and mixtures of minerals are the reason for the misclassification of the second sample (kaolinite) [Geerken, 1992]. Mineral mixtures will be added to the spectral library in future.

8 CONCLUSION

This paper presents a method to identify minerals in hyperspectral data sets. The use of Neural Network Classifiers for detecting minerals based on a spectral library is explained. Further research will consider mixtures of minerals and more characteristic features than only absorption features to improve the accuracy of the image classification. The quality of diagnostic analysis of GER data is still limited due to insufficient SNR's.

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sed minerals for the classification within the VNIR/SWIR bohnezite and goethite were used. Three neutral classes were generated and used for each classification step.
Two MLP-Networks have been designed. The first Network (SWIR) was composed of 23-10-14 neurons and the second (VNIR/SWIR) of 52-15-16 neurons. The Networks were trained with 2000 epochs, while the sensorspecific signature of each mineral was continuously changed. During several learning simulations the online-method was superior to the offline-methods.

7 RESULTS

To test the efficiency of the Networks, all training patterns were reclassified. The average accuracy for a correct class decision has been 92% for the SWIR-Network and 88% for the VNIR/SWIR-Network, although several minerals show a quite similar spectral behavior.

About 25% of the image's pixel have been classified. All other pixels show no specific geological characteristics and have been assigned to a neutral class. Several samples have been analysed to proof the decisions of the Networks. In all cases the Networks assigned the most matching signature from the spectral library based on the extracted features. Figure 3 shows the spectra of several classes and their corresponding spectra of the database.

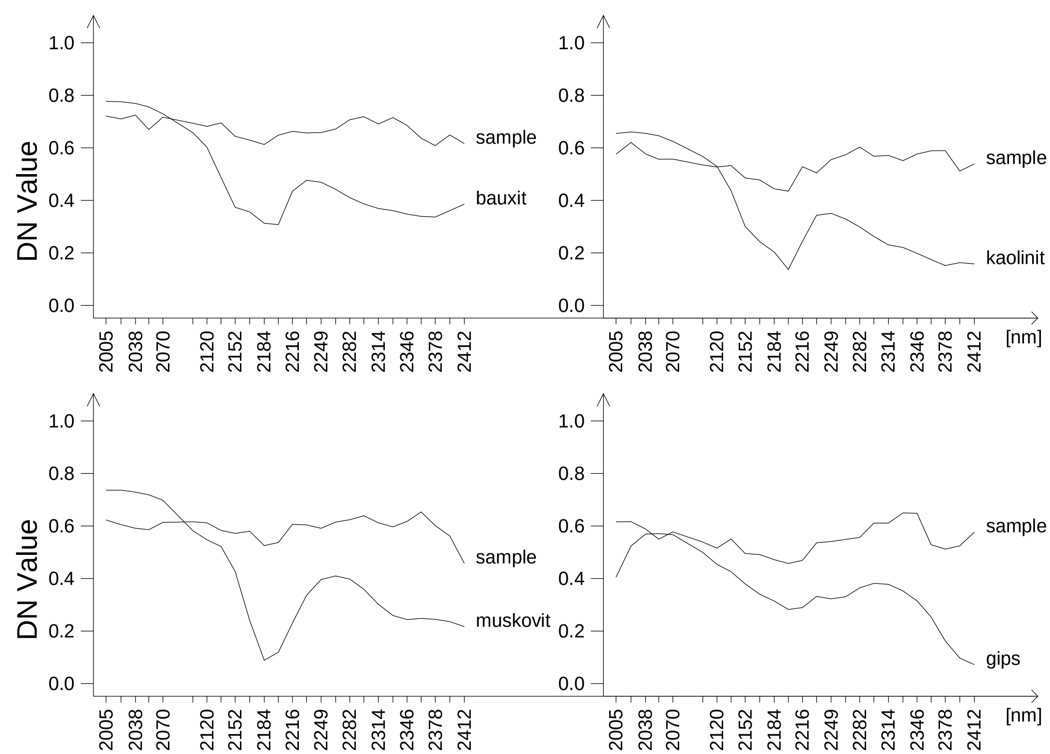

Figure 3: Spectrum of samples and best class decisions.

Although the NN provides a good classification technique for hyperspectral data, the results do not always correspond with reality. Misclassification is caused by masking or changing characteristic signature due to sensor characteristics and/or due to physical effects such as mineral mixtures,

5 TEST-SITES AND INSTRUMENTATION

The Makhtesh Ramon an anticline structure is located in the Negev, in Israel, about 70 km SSW of the Dead Sea. In it's extension it is 40km long and has a varying width of 6 to 9 km. The M. Ramon is a deeply eroded anticlinal structure characterized by a high variety of Mesozoic formations. The test area shows several mining localities for gypsum, kaolinite and bauxite, and is marked by a syenitic stock separated in several blocks of different hydrothermally altered zones ([Mazor, 1984]). Data of this area were acquired during the European Imaging Spectroscopy Airborne Campaign (EISAC) in July 1989. The instrument used, was a GER-II (Geophysical Environmental Research) electromechanical scanner providing 63 channels in three modules ([Collins a. Chang, 1982]).

GER covers the VIS/NIR and SWIR range namely VNIR, SWIR-1 and SWIR-2 with a nominal spectral resolution of 12.37nm, 120nm and 16.22nm respectively. Data are recorded with a radiometric resolution of 16 bits. The IFOV of 3.3mrad results in a spatial resolution of 13.44m at a flight altitude of 15000 feet.

Dark current and giro correction was applied to the raw data. Geometric distortions in scan-direction were corrected using a simple cosine function. Radiometric correction was applied using the flat field method. 16 to 8 bit data conversation was performed by cutting the histograms at the 0.2bit frame ([Kaufmann et. al., 1990]).

6 CLASSIFICATION

Several problems demand a complex classification scheme. Due to the fact that the used signal to noise ratios are not true for a single pixel an unsupervised classification based on a minimum distance classifier was applied selecting pixels in the neighbourhood of a central pixel which are spectrally similar. It is assumed that the used SNR's are valid for the mean spectrum of these pixel groups. Furthermore more precise spectral details are present in the mean spectra. The second problem results from the spectral behaviour of the minerals. While spectral features are relatively constant within the SWIR-range $[2000 - 2400nm]$, features within the VNIR-range $[400 - 800nm]$ based on iron absorption bands are very variable in nature. This is not yet considered in the used spectral library. Thus, classification is performed in two steps. In the first step only information of the SWIR-range is used. All unclassified pixels are reclassified in the second step using additional information of the VNIR-range. A more simple classification scheme could be used by the direct use of image data as learning patterns. However this would require very precise knowledge of the geology of the investigated area.

Another problem arises from the use of the MLP-Network. One characteristic of the MLP is, that the approximation of the classification function is based on a seperation of the feature space via hyperplanes and not on local receptive fields, like the Radialbasisfunctions Networks (RBFN) [Lee a. Kil, 1991] do. To force the network to a more precise description of the classes, several neutral classes with no specific spectral behavior are generated and added to the learning process. This will be unnecessary when using an RBFN in future.

Following minerals were used for the classification within the SWIR range: alunite, muscovite, bauxite, kaolonite, illite, gipsum, magnesite, hematite, dolomite and calcite. As additional iron ba-

4 INPUT DATA (SPECTRAL LIBRARY)

Diagnostic analysis of hyperspectral data is mainly based on the existence of characteristic absorption features. The position and shape of the minima can be used to distinguish between a number of e.g. minerals in arid areas. Spectral features, evidenced by bands or changes in the slope of spectral curves, appear as a result of either electronic or vibrational processes. The visible (0.4- 0.75m) and near infrared (0.7-1.15m) range is characteristic of spectral features introduced by transition elements. The most important transition element for terrestrial remote sensing is by far the iron in the bi- and trivalent state. Iron produces electronic features that are mainly caused by charge transfer bands and crystal field transitions ([Hunt et. al., 1971]). They are rather broad, and their minima vary in dependence of the mineral species.

The short-wave infrared range between 1.1 and 2.55m is of considerable interest, because it provides more diagnostic spectral information about the composition of minerals and rocks than the VIS and NIR range. Phyllosilicates, carbonates and some sulphates show strong, relatively sharp and distinct absorption features in this section of the spectrum. These absorptions are due to vibrational processes (overtones and combination tones of the fundamental modes occurring in the mid-infrared) of anion groups and molecules such as OH^-, CO_3^{2-} and H_2O ([Hunt a. Salisbury, 1970] [Hunt a. Salisbury, 1971]). Atomic groups form independent oscillatory units like Al$-$OH, Mg$-$OH and CO_3. Minerals containing either of these groups show characteristic frequencies whose positions are determined by neighbouring molecules. Minerals containing Al$-$OH$-$or Mg$-$OH groups produce features around 2200nm and 2300nm respectively. Absorption bands within one group are located closely together. Thus, to be able to separate and identify the mineral species a high spectral resolution at sufficient signal to noise ratio is needed.

To normalize for the broad shape of the measured spectra and to focus on the absorption features, hull-functions (Figure 2) of the spectra are calculated, and information of the distances between the spectrum and its hull extracted. This values are scaled to a range between [0,1], since sigmoid output functions are used in the NN. In this way each band of the sensor is adjusted to an input node.

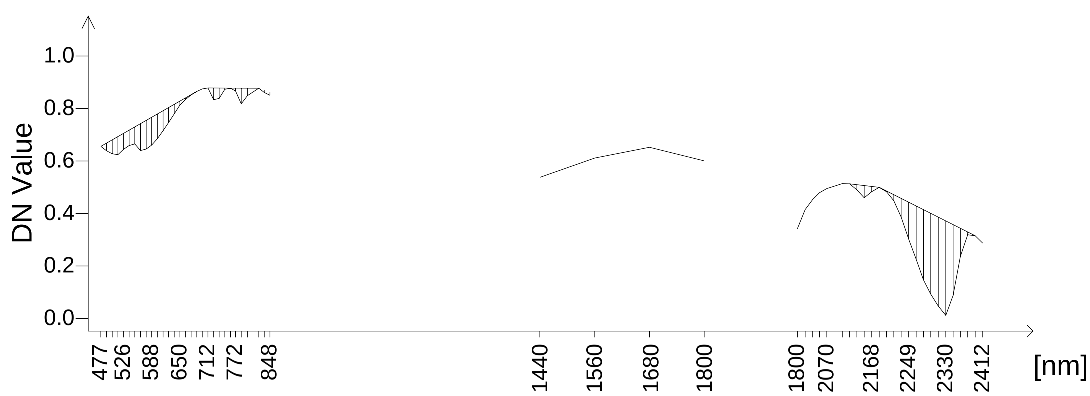

Figure 2: Spectrum of calcit with hull-function.

sensor systems. On the other hand using the parameters of an existing sensor system the NN can be used to classify an image which is the subject of this paper.

3 NEURAL NETWORKS

At the current point of development, Neural Networks have still less in common with their original biological model, but are similar to statistical techniques, like generalized linear models, discriminant analysis, principle componets etc. ([Sarle, 1994]). This is especially valid for the Multilayer-Perceptron (MLP), a feedforward network, which is used in NESSI. Hornik([Hornik, 1989]) has shown, that a MLP with one hidden layer can be compared as a universal function approximator.

The MLP shows a very simple structure. Every node of the current layer is connected to every node of the following layer. The number of input nodes depends on the number of possible features, given by the sensor definition. The number of output nodes is equal to the number of classes to be classified. The number of the hidden nodes however has to be chosen dynamically according to the given problem. There exists no rule of thumb.

The signal transformation in a network is characterized by a synaptic summation (1) of each neuron: the summation of the input signal x and the neuron's weight array w, in combination with a nonlinear transformation function $g(z)$, for example a sigmoid function (2) and a bias term b.

$$y(x) = g(\sum_{j=1}^{input} w_j x_j - b) \tag{1}$$

$$g(z) = \frac{1}{1+e^{-z}} \tag{2}$$

During the supervised learning phase the weights are dynamically changed to approximate the unknown classification function. This is done by a minimisation of an error-function. In the last years an enormous number of various techniques has been described and compared (e.g. [Jervis a. Fitzgerald, 1993]) to improve the convergence of this procedure. They all have in common a special assumption about the unknown surface of the error-function. The success of a technique therefore mainly depends on the conformity to the real problem. So three different methods have been implemented. Beside the traditional backpropagation algorithm with momentum term ([Rummelhart, Hinton a. Williams, 1986]), as an online version, we have also implemented the Scaled Conjugate Gradient Algorithmus ([Moeller, 1993]) and the RPROP algorithmus ([Riedmiller a. Braun, 1993]), as offline versions. One important advantage of the last two techniques is, that they didn't need any user specified parameter. Online training means, that the weights are changed after every training pattern, in opposite to the offline version, where the weights are changed only after each training epoch.

therefore prefer or disqualify a certain method.
In the case of classifying hyperspectral data with a linked spectra library a huge amount of example data and variable sensor characteristics are required and postulates the use of the Neural Network technique.

2 NESSI

A software for Neural Evaluation of Spectral Signatures (NESSI) was developed for this purpose. It consists of three components (see Figure 1):

- a linked spectral library
- a sensor description database
- the Neural Network (NN) itself.

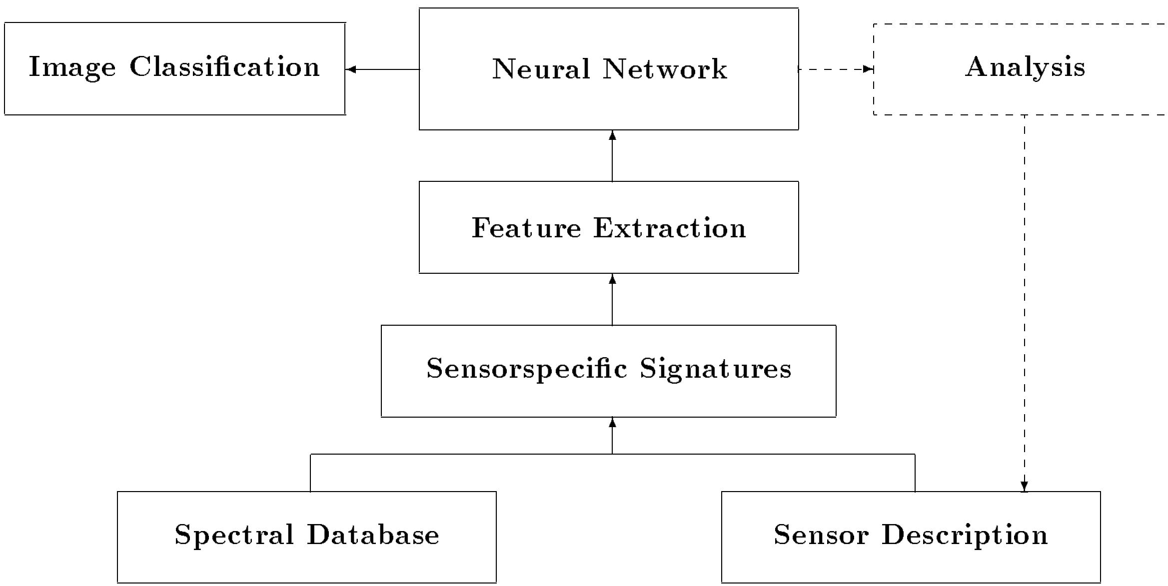

Figure 1: Global scheme of NESSI.

Standard minerals have been measured spectrally in the range of 400 to 2500nm using a Perkin-Elmer-Laboratory-Spectrometer with a resolution of 1 nm. The spectra were used to built up a library which is linked to NESSI. A second database containing sensor specific information such as number of bands , band centers, bandwidths and mean SNR's of bands is used for describing the sensor characteristics. The third component is the classification unit performed by a Neural Network. Sensor specific signatures are generated calculating the reflectance means within the bands as well as folding the spectra with gaussian or random noise defined by the mean SNR's. A feature extraction tool using a segmentary hull function is used to feed the NN with training patterns. A well trained NN gives the opportunity to analyze the results due to the used inputs such as class separation in dependence of sensor improvements. Thus, it can also be a valuable tool for defining

DIAGNOSTIC ANALYSIS OF HYPERSPECTRAL DATA USING NEURAL NETWORK TECHNIQUES IN COMBINATION WITH SPECTRAL LIBRARIES

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ABSTRACT

The advantage of hyperspectral data sets with its ability for diagnostic analysis is widely recognized in different fields of application. Real time spectra extraction in combination with high spatial information can significantly improve the accuracy of mineral identification.

Insufficient signal to noise ratios as well as mixed pixel/signatures decrease the accuracy to diagnostic mineral identification. Thus, it is often difficult to link extracted spectral signatures to distinct minerals.

In this context a software for Neural Evaluation of Spectral Signatures (NESSI) was developed. The advantage of the neural network technique in combination with spectral libraries has been proven by noise folded spectra of well defined mineral mixtures. The technique was then applied to natural rock types and GERIS hyperspectral image data of the Maktesh Ramon test-site located in Israel.

The network guaranteed a relative precise identification of the most matching signature. The average accuracy for a correct class decision was 92% within the SWIR-network and 88% within the VNIR/SWIR-network. About 25% of the image could be assigned to minerals of the spectral library. Misclassifications can mostly be traced to the poor SNR of the GER data and the missing of mineral mixtures in the spectral library.

1 INTRODUCTION

Various techniques, like Statistical Methods, Fuzzy Logic, Evidence Based Methods, Semantic Networks or Neural Networks have been successfully applied analyzing and classifying remotely sensed data. The question which technique is the most suitable for a certain application depends on the problem itself. Requirements, assumptions and objective demand a special proceeding and