Hyperspectral Image Generation, Processing and Analysis

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Abstract

Hyperspectral reflectance data are utilised in many applications, where measured data are processed and converted into physical, chemical and/or biological properties of the target objects and/or processes being studied. It has been proven that crop reflectance data can be used to detect, characterise and quantify disease severity and plant density.

In this thesis, various methods were proposed and used for detection, characterisation and quantification of disease severity and plant density utilising data acquired by hand-held spectrometers. Following this direction, hyperspectral images provide both spatial and spectral information opening for more efficient analysis.

Hence, in this thesis, various surface water quality parameters of inland waters have been monitored using hyperspectral images acquired by airborne systems. After processing the images to obtain ground reflectance data, the analysis was performed using similar methods to those of the previous case. Hence, these methods may also find application in future satellite based hyperspectral imaging systems.

However, the large size of these images raises the need for efficient data reduction. Self organising and learning neural networks, that can follow and preserve the topology of the data, have been shown to be efficient for data reduction. More advanced variants of these neural networks, referred to as the weighted neural networks (WNN), were proposed in this thesis, such as the weighted incremental neural network (WINN), which can be used for efficient reduction, mapping and clustering of large high-dimensional data sets, such as hyperspectral images.

Finally, the analysis can be reversed to generate spectra from simpler measurements using multiple colour-filter mosaics, as suggested in the thesis. The acquired instantaneous single image, including the mosaic effects, is demosaicked to generate a multi-band image that can finally be transformed into a hyperspectral image.

Keywords: hyperspectral imaging, colour filter mosaics, remote sensing, crop reflectance, surface water quality, disease severity, plant density, linear system of equations, waste water detection, chlorophyll a, suspended particulate matter, weighted fixed neural networks, weighted incremental neural networks, camera spectrometer

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urn:nbn:se:uu:diva-5905 (http://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-5905)
To my dear parents
and my love Asma.
List of enclosed papers

The thesis is based on the following publications, which will be referred to in the text by their Roman numerals:


All published papers are reproduced with permission from the publisher. The papers in this thesis have been checked for errors and thus differ somewhat from the published versions. The author has significantly contributed to the work performed in all joint papers.

The work in this thesis was partly financed by a research grant from the Swedish National Space Board (SNSB).
Related work

In addition to the papers included in this thesis, the author has also written or contributed to the following publications:


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Introduction and objectives

Everything around us has specific colours characterising its physical, chemical and/or biological properties. Actually, the colour we see is the little portion of incoming electromagnetic signals that our eyes are able to detect and deliver to our brain for analysis and interpretation giving a result which depends on our gained experiences. Our powerful brains succeed in extracting meaningful information from these, in terms of our current understanding and technology, rather poor signals.

Today’s remote sensing technology can detect a much larger portion of the electromagnetic spectrum, but there is still a need for new and more efficient methods for extracting as much useful information as possible from captured signals.

One of the most important fields of image analysis research is analysing remotely sensed images acquired by satellite and airborne systems. Remote sensing offers the opportunity to study a relatively large region on the Earth by a single image. In addition, satellite and airborne remote sensing analysis systems offer efficient and environmentally friendly non-destructive techniques.

One of the objectives of this thesis is to analyse these kinds of images in a way that takes into account the entire content of available data to extract as much useful information as possible from these data. The statistical approach is one of the most commonly used and efficient techniques for this purpose, where it is allowed to have data affected by some kind of disturbing factors. This is important because it is impossible, besides that it is impractical, to make sure that we have exactly the same conditions when acquiring satellite images at different times, even when using the same instrument. Weather conditions and variations in the sensitivity of the instrument are the main disturbing factors. Hence, it is important to try to compensate for all known disturbing factors to obtain data of more uniform quality, i.e. normalised noise free data. Radiometric calibration and atmospheric correction are usually employed to convert these data into ground reflectance data; i.e. as if the measurements were done near the target objects, e.g., by using a handheld instrument. Therefore, it sounds reasonable to also study real ground reflectance measurements to be able to evaluate the correction tasks and to find out how the analysis can be performed in the ideal case and what parameters should be taken into account. Handheld spectrometers were used to acquire crop and water-sample reflectance spectra in addition to ground-truth meas-
urements of the crop or water quality parameters of interest. These data were employed to develop and evaluate algorithms for estimation of desired parameters using spectral data. The gained results were transformed to the more complex case; i.e. the “distant” remote sensing.

Remote sensing systems usually acquire very large image data sets, which require fast and efficient analysis techniques. The statistical methods are good at looking at the data to know which part of it and which features contains the useful information that we are interested in. This little portion and features are what we actually need to focus on, because by using only them, we still get as much useful information as possible, as if we had used the whole data set.

It is obvious that less computational power and memory requirements are needed when reducing the amount of data we have to process. Statistical methods look at the statistical properties of the data samples to decide which of them are useful. On the other hand, many statistical methods exist for finding basis vectors, on which our image data can be projected to produce useful components. These methods are referred to as transformations (such as Principal Component Analysis PCA [1] and Independent Component Analysis ICA [2, 3]). The difference between these methods is in the choice of a suitable set of statistical properties of the data samples that are considered when finding the basis vectors. The next step is to study these basis vectors to try to build “smarter” ones that can be used for both obtaining the best projections and extracting useful information. The approach referred to as Feature Vector Based Analysis FVBA [VI] was developed to suggest a uniform framework to achieve more efficient statistical analysis of high dimensional data, e.g. hyperspectral images.

To further reduce the usually very large remotely sensed images, new techniques were developed to attack this problem. Self organising and learning neural networks, that can follow and preserve the topology of the data, have been shown to be an efficient tool for data reduction. More advanced variants of these neural networks, referred to as the weighted neural networks (WNN) [XII], were developed in this thesis and used to generate fuzzy representations of hyperspectral as well as ordinary image data. Furthermore, a variant of WNN, referred to as the weighted incremental neural network (WINN) [XI], was developed and employed for efficient reduction, mapping as well as clustering of large high-dimensional data sets, such as hyperspectral aerial images of inland waters, hyperspectral microscopic images of prostate cancer tissues, as well as hyperspectral crop reflectance data.

However, one serious limitation of today’s conventional multi- and hyperspectral imagery systems is the need for scanning time to be able to acquire the whole image cube, which contains huge amount of data needing large memory capacity. Sophisticated onboard data reduction combined with image processing and analysis can be employed so that only a derived product is down linked, but original image data will be lost then. In this thesis, a
novel cost-effective technique, that solves the problems mentioned above, is suggested. The system has no moving parts and the whole multi- or hyperspectral image cube is acquired instantaneously, making it ready to record multi- and hyperspectral digital video.

The basic idea behind this technique is the observation that it is possible to go in the opposite direction of the analysis procedure presented previously, and generate spectra of reasonable resolution from simpler colour measurements utilising low-cost broad-band colour filters. A set of measured colour-filter responses to exactly the same incoming light, can be used to estimate the spectrum of that light. A multiple filter mosaic, with higher spatial resolution than the imaged scene, can be used to register an instantaneous single (scalar) image including the mosaic effects. Demosaicking this image generates a multi-band image that can finally be transformed into a hyperspectral image. Least-squares solution of linear system of equations was utilised to find the required transformation coefficients to be able to generate spectra from filter response measurements. The small size of the initially acquired single images makes this approach useful for applications, such as satellite based hyperspectral imaging systems and telemedicine, where the images need to be transferred either on- or off-line to distant places to be saved and/or processed.

The results presented previously were derived through research performed within four projects as follows.

Information extraction from remotely sensed hyper spectral images of Swedish inland waters

The aim of this project was to develop algorithms for the estimation of surface water quality parameters for inland waters using remotely sensed hyperspectral images. The hyperspectral images, used in this project, were acquired using the compact airborne spectrographic imager (CASI), during a CASI campaign in August 1997, over Lake Erken, north-east of Stockholm, and over the region of Norrsundet, north of the city of Gävle, Sweden. Field measurements were collected over Lake Erken at approximately the same time of recording the CASI image.

The work was based on the fact that a substance can be characterised and recognised by its unique spectral signature. Hyperspectral imaging systems can provide a sufficient number of narrow spectral bands to be able to accurately determine the spectral response at each pixel in the image. Because of the usually low spatial resolution of remotely sensed images, each hyperspectral pixel (which represent a spectrum) in the image can be considered as a mixture of reflectance spectra of several substances found in the corresponding imaged region. Independent Component Analysis (ICA) [2, 3] and
Principal Component Analysis (PCA) [1] have been used to transform the hyperspectral image as a first step to get a new set of data that is more suited for further processing than the original image. The next step is to interpret and use the ICA or PCA results efficiently. This can be achieved by using a new technique called Feature Vector Based Analysis (FVBA) [VI] which has been developed at the beginning of this project.

The outputs of the transformation step (which are a number of basis vectors and projections of original data on these vectors) are considered as so called Component-FeatureVector pairs in the subsequent FVBA step. The FVBA task itself is application dependent. But, the common idea of FVBA is to look at the (simpler) feature vectors in order to understand the corresponding (more complicated) components. FVBA can be used for four main types of applications [VI]. In the first two, either well-defined feature vectors or well-defined components are available. The other two types of applications are feature extraction and classification. When studying hyperspectral images of Swedish inland waters, the obtained feature vectors and the corresponding components represent spectral signatures and the corresponding weight-coefficients images (e.g. the relative concentration maps) of the different constituting substances. Linear combinations, of either the spectral feature vectors or the component images, are employed to obtain results that are as close as possible to well-known spectra or maps, respectively, and the corresponding maps or spectra will provide the required information [V, VI].

Descriptive spectral signatures, characterising the effect of each water quality parameter on the spectral properties of the water, can be obtained by, at first, normalising the spectral data in a special way [III, IV], then assuming a linear relationship between normalised data and water quality parameter. The solutions of these linear systems of equations represent useful descriptive spectral signatures [III] that can be used to estimate water quality parameters [III] and to detect and classify anomalous spectra, e.g. identifying industrial waste water [IV]. A linear statistical approach was also used to determine water quality parameters from hyperspectral data [III]. The work resulted in the publications [III, IV, V, VI].

Information extraction from hyperspectral crop reflectance data

This project aimed to develop algorithms for the estimation of crop status parameters in wheat crops using hyperspectral crop reflectance data. The hyperspectral data and the corresponding measurements of crop-status parameters used in this project were provided by Anders Larsolle (Dept. of Biometry and Engineering, SLU, Uppsala, Sweden) who also contributed to the resulted publications of this project [VII, VIII, IX].
The motivation for this work was the observation that the impact of various plant status parameters on crop reflectance can be measured both in broad band vegetation indices and in local characteristics of the reflectance spectra. The goal was to use the whole spectrum in the objective examination of how different parts of the spectrum contribute in describing plant status parameters (e.g. disease severity in wheat). A reference data set, consisting of hyperspectral crop reflectance data (i.e. spectra) and the corresponding measurements of plant status parameters, was required. Two approaches were employed to achieve the goal of this project. The first one used FVBA [VII] based on PCA and ICA. High correlations were found between measured and estimated disease severity in the crop. The effects of increased disease severity could be easily observed from the resulting disease-specific spectral signatures. In the second approach [VIII, IX], hyperspectral data were first normalised into zero-mean and unit-variance vectors by performing various combinations of spectral- and band-wise normalisations. Then, a nearest neighbour classifier was used to classify new data against reference data. Finally, the corresponding signatures describing the studied plant status parameters (disease severity and plant density), were computed using a linear transformation model. Slightly better correlations than the first approach were obtained. The low computational load of this approach makes it suitable for real-time on-vehicle applications.

Image data reduction and segmentation by using neuro-fuzzy systems

The aim of this project was to achieve methods for “fair” data reduction; i.e. the reduced data set is equivalent to the original one. Another desired functionality was to discard outliers. In other words, a “democratic” approach was required. Therefore, new neuro-fuzzy systems (referred to as Weighted Neural Networks, WNN [XIII]) which could characterise the distribution of a given data set were developed. The basic idea was based on the famous Hebb's postulate [21] stating that the connection between two winning neurons gets stronger. The WNN [XII] algorithm produces a net of weighted nodes connected by weighted edges. The resulting weighted graph provides a fuzzy representation of the topology of the data. A fuzziness factor, proportional to the connectedness of the net, is introduced in the system. Two main types of WNNs were developed: incremental self-organising (referred to as Weighted Incremental Neural Networks, WINN) [XI] and fixed or grid-partitioned (referred to as Weighted Fixed Neural Networks, WFNN) [X].

In the WFNN, [X], a number of zero-weighted nodes are uniformly distributed in input space (of given data). Then, weights are assigned to these
nodes, where a relatively higher weight corresponds to a relatively denser region of the data set. Weighted connections are established between neighbouring nodes, where the weights are also proportional to the local density of input data.

In the WINN, [XI], the model is built by successive addition, adaptation, and sometimes deletion of graph elements (i.e., nodes and edges), according to suitable strategies, until a stopping criterion is met. The algorithm begins with only two nodes connected by an edge, then new nodes and edges are generated and the old ones are updated (and sometimes deleted) while the learning process proceeds until a certain stopping criterion is met. The result is a weighted graph preserving the topology of the input data set. The WINN could robustly process data of various dimensionalities [XI, XIII, XIV]. A fuzzy clustering algorithm employing the WINN was also developed [XI] and used for hyperspectral image segmentation [XI, XIII], as well as segmentation of colour images [XI, XIV].

New approach to instantaneous multi- and hyperspectral imaging

This project was driven in collaboration with Prof. Fredrik Bergholm at Centre for Image Analysis.

The reason of starting this work was the lack of low-cost user-friendly instantaneous multi- or hyperspectral imagers. Hence, the aim was to design a cost-effective system that could generate instantaneous multi- or hyperspectral 2D-images. The basic idea was to equip the imaging sensor array with multiple colour mosaics (in the same way of constructing single-chip colour digital cameras), to make it capture more spectral information (but, sacrificing spatial resolution somewhat). However, integrating colour mosaics onto the image sensor chip must be done in the digital-camera manufacturer’s laboratory, which is slightly inconvenient for people involved in remote sensing, photogrammetry and/or image analysis, who rather would like to use a non-invasive technique, where technical details on how the image sensor chips is built-up should stay a secondary concern. In a pilot study, the possibility of placing the filter mosaic (a thin plate) in some favourable position in the path of light through the lens system was investigated. A patent application (financed by Uppsala University Holding Company, UUAB) on a multi- and hyperspectral imaging system using multiple colour mosaics has been filed [4].

The work also resulted in two manuscripts [I, II] (submitted for journal publication) discussing the accuracy and robustness of transforming measured multiple colour-filter responses into spectra of as high spectral resolution as possible. Linear systems of equations were employed to perform this
transformation. In [I], error sensitivity of the linear transformation approach (referred to as the statistical method) was compared to the pure measurement method (where the used filters’ sensitivity curves were known), and a simulation study confirmed the robustness and usefulness of the linear transformation method for generating spectra from multiple filter responses.

This method was used in [II] to transform measurements obtained using an imaging system employing a multiple colour-filter mosaic (a simple prototype) into spectra. Promising results were obtained despite the shortcomings of the prototype.

The resulting system, including the hardware and the algorithms, was called the camera spectrometer.
Multiple colour mosaics for instantaneous hyperspectral imaging

Today’s conventional multi- and hyperspectral imaging systems can not capture instantaneous images. The scene must be scanned either spatially or spectrally to be able to collect the whole image hypercube. Another disadvantage that can be noticed is the huge amount of data which these systems capture and need to immediately transfer to distant places to be stored or processed. This is why it is more economic to process the data onboard the satellite and send only the results to the ground station. The high expenses of such systems discourage investments in this relatively new, but extremely useful field.

Multi- and hyperspectral imaging technology is being increasingly used in environmental monitoring, biological, earth science, transportation, precision agriculture, and forestry applications to deliver data and information. Ground-based, attached to microscopes or telescopes, hand-held, airborne and spaceborne systems are used to observe scenes ranging from microscopic objects (e.g. cancer cells) up to planets and galaxies.

Fortunately, an ordinary monochrome or colour digital image sensor (a digital camera) may by simple means be converted into a camera that can capture much more spectral information, but with some reduction in spatial resolution. The resulting multi- or hyperspectral camera is as quick and user friendly as the underlying digital camera. The resulting multi- or hyperspectral image data are as small (in storage size) as the corresponding single images delivered from the image sensor array.

The captured images must be demosaicked then transformed into multi- or hyperspectral images. The most attractive transformation approach here is the linear model due to its simplicity and low computational load.

The new multi- or hyperspectral imaging approach was presented in papers [I and II].

Paper I

This paper addressed the feasibility of two different transformation approaches that can be used to transform multi-channel data, produced when
the incoming light is filtered by multiple filters, into multi- or hyperspectral
data.

The signal captured by an image sensing element covered by two overlap-
ing colour filters is given by the integral:

\[ \int \rho(\lambda) \ T(\lambda) \ I(\lambda) \ d\lambda = \int \rho(\lambda) \ T_1(\lambda) \ T_2(\lambda) \ I(\lambda) \ d\lambda, \quad (1) \]

where \( \lambda \) is the wavelength, \( \rho(\lambda) \) is the sensitivity function of the sensor, \( T_1(\lambda) \) and \( T_2(\lambda) \) are the transmission functions of involved colour filters, and \( I(\lambda) \) is the incident light signal. The sensitivity function of the sensor element covered with this multiple filter is given by:

\[ \rho(\lambda) \ T_1(\lambda) \ T_2(\lambda). \]

For simplicity, \( \rho \) is usually set equal to one.

For example, in the case of using the two overlapping mosaics shown in
figure 1, nine different multiple colour filters are formed by the overlap-

The relation between a spectrum vector \( x \) and the corresponding image
responses vector \( y \) is assumed to be the linear system of equations

\[ A \ x = y \quad (2) \]

where \( A \) is a matrix containing the multiple-filters’ sensitivity function vec-
tors on its row. The solution of this system is

\[ x = A^T (A \ A^T)^{-1} \ y \quad (3) \]
which is using the pseudo inverse of $A$, which has been derived from the requirement that the basis functions of the spectra coincides with the basis functions of the sensitivity functions, which must be known. This method will be referred to as the pseudo inverse method.

A more traditional method assumes a linear relation $T$ between a multi-channel data vector $y$ and the corresponding spectrum vector $x$, so that

$$x = T y$$  \hfill (4)$$

where matrix $T$ is estimated by solving the system of linear equation

$$X_t = T Y_t$$  \hfill (5)$$

where $X_t$ and $Y_t$ are two training-data matrices containing (in their columns) a number of $x$-vectors and the corresponding $y$-vectors, respectively. This method will be referred to as the statistical method.

Figure 2. (a) Sensitivity transmission functions (STFs) of the original single colour filters. (b) STFs of the filter set in case (6). (c) STFs of the filter set in case (7).
Simulations were performed on a synthetic data set consisting of pairs of spectra, measured by a conventional spectrometer, and the corresponding image responses, generated by filtering these spectra through a set of hypothetical multiple colour filters, as shown in figure 2. Spectra from printed colour charts were measured in daylight. These data were utilized when investigating the sensitivity and performance of the two methods.

The following multiple filter sets were considered

\[
A_{(2)} = [R, G, B, MR, MB]^T \tag{6}
\]
\[
A_{(1)} = [R, G, B, MR, MB, YR, YG]^T \tag{7}
\]

For the pseudo inverse method, the relation between the condition number of \( A \), \( \text{cond}(A) \), and various choices of the used simulated multiple filters, was studied. The results showed, in the case of (6), that the error magnification was in the interval 4 to 7. However, in the case of (7), much higher \( \text{cond}(A) \) values were obtained indicating that this method was not useful for this case.

For the statistical method, the conclusion was that the estimation accuracy of reconstructed spectra, mainly depended on the spectral characteristics and number of utilised multiple colour filters (the more the better) as well as the choice of the training data set so that all possible data-sample classes were represented by the training data set, otherwise, the estimation error would increase.

Figure 3. Comparison between the relative estimation errors of the two cases.

Figure 3 shows a comparison between histograms of the relative estimation errors for the cases of (6) and (7). In this figure, the superiority of case (7) can easily be noticed.

Finally, figure 4 presents comparisons between four measured spectra and the corresponding reconstructed spectra (by using the statistical method), with relative estimation errors ranging from 0.8% to 13.7%.
Paper II

This paper presented an experimental evaluation of a camera spectrometer system comprising an optical device equipped with a microscopic CMYT colour filter mosaic attached to a colour digital camera (with an own RGB mosaic), and using the linear statistical method described by equations (4) and (5).

Figure 5 presents a simplified construction of an optical device that can be attached to a digital camera to convert it into a multi-channel camera.

Figure 6 illustrates how the two overlapping mosaics, the RGB mosaic (which is embedded inside the camera) and the external CMYT mosaic (inserted into the optical device) cooperate to produce a multiple-layer colour-filter mosaic, consisting of 12 different multiple filters: R, G, B, CR, CG, CB, YR, YG, YB, MR, MG and MB.
At first, the image-areas covered by the mosaic-element colour-filters, were segmented using image analysis techniques. Then, the mosaic-element re-
responses were extracted to build the corresponding multi-channel image, which was finally transformed into a multi- or hyperspectral image.

Figure 7 shows a histogram of the relative estimation errors of 1000 experiments.

Figure 8 presents comparisons between four estimated reflectance spectra and the corresponding reflectance spectra measured by a conventional spectrometer. The relative estimation errors range from 6% to 51% for the selected cases.

The results in figure 7 are much worse than those of the simulation study presented in figure 3. However, the shapes of the curves of the estimated reflectance spectra follow the shapes of the corresponding measured spectra, as can be noticed in Figure 8. Therefore, using a more controllable camera and performing more carefully calibrated measurements will probably generate much better results.
Hyperspectral data analysis

Hyperspectral reflectance data can be used to estimate physical, chemical and/or biological properties of the target objects in the imaged scene, offering fast efficient and environmentally friendly non-destructive techniques. Hyperspectral imagers are being increasingly used in environmental monitoring and precision agriculture to deliver data rich in information that must be extracted and used in efficient ways, to be able to achieve alternative methods that are at least as efficient as the currently used techniques which are usually destructive, expensive and time consuming.

In this thesis, these kinds of data were used to monitor surface water quality in inland waters, detect industrial plumes in water, estimate disease severity and quantify plant density in wheat crops. Descriptive spectral signatures were extracted to be used as fingerprints to identify the various water quality or plant status parameters.

The developed methods were presented in papers [III - IX]. The data used in papers III, IV and V were provided by Ass. Prof. Tommy Lindell, Centre for Image Analysis, Uppsala University, Sweden.

Paper VI

This paper presents a unified framework, referred to as Feature-Vector Based Analysis (FVBA), for analysing high-dimensional data. FVBA suggests to first transform the data using an appropriate technique that can provide useful results, then process these results in an efficient way to be able to extract desired information. The outputs of the transformation step (which are a number of basis vectors and projections of the original data on these vectors) are considered as so called Component-FeatureVector pairs, and the basic idea of FVBA is to investigate the Feature Vectors to understand the corresponding, usually more complex, Components.

Two widely used transformations, Principal Component Analysis (PCA) [1] and Independent Component Analysis (ICA) [2, 3], were used to illustrate how FVBA works, with detailed examples on using FVBA based on ICA. FVBA can be used for four main types of applications.

Intuitively, two types of applications can directly be identified where either well-defined Feature Vectors or well-defined Components are available or should be present in the data, and the corresponding Components respec-
tively *Feature Vectors*, which are the desired information, can be directly obtained.

FVBA can also be used for other types of applications, such as feature extraction and classification, because the system of linear equations, that describe the transformation, can be considered as a special neural network trained or optimised by performing the transformation. In this case, the *Components* and the *Feature Vectors* can be considered as outputs and weights of this neural network.

Let’s look at an example on using FVBA for feature extraction and classification. Consider the case of having two data sets, $X_1$ and $X_2$, belonging to two different classes, class I and class II. Figure 9 illustrates the feature extraction process. At first, ICA is applied to the data $X$, then linear combination of the feature vectors which produces a feature vector that looks like the one in Figure 9, is found. This feature vector highlights $X_2$, i.e. class II. Hence, the corresponding component $C_{\text{class II}}$ represents some special features that make $X_2$ (class II) recognisable with respect to $X_1$ (class I). A subsequent analysis must be done on this component to figure out what those special features are.

![Figure 9. Feature Extraction.](image)

Thereafter, classification of new data $X_{\text{new}}$ can be performed by solving the equation

$$X_{\text{new}} = FV_{\text{new}} \ C_{\text{class II}} \quad (8)$$

The resulting feature vector, $FV_{\text{new}}$, is the desired classification result, as illustrated in figure 10.

![Fig 10. The new resulting feature vector, FV_{new}.](image)
The number of the components, $C_{\text{class}}$, that act as discrimination functions must be equal to the expected number of classes of the data. This is a supervised classification, because the components $C_{\text{class}}$ are chosen by the user. The linear equation system in equation 8 can be seen as a special neural network whose weights, inputs and outputs are represented by $FV_{\text{new}}$, $X_{\text{new}}$ and $C_{\text{class}}$, respectively.

Papers IV and V

Remotely sensed hyperspectral image data has been acquired, by using the Compact Airborne Spectrographic Imager (CASI), over the region of Norrsundet (fig. 11) in Sweden, during a CASI-campaign in August 1997. The waters in this region were affected by an outlet from the small Hamrängeån river and the waste water outlet from the Norrsundet paper-pulp industry, as shown in fig. 11. Of the acquired CASI spatial-mode image, which has 10 spectral bands and spatial resolution of 4×4 meters, a small portion of size 400×400 pixels was selected to be used in this work. The sub-image, which covers the area of investigation, is shown in fig. 12a. Table 1 presents the band settings of the CASI spatial-mode which are similar to those of the MERIS sensor on Envisat.

<table>
<thead>
<tr>
<th>Band No</th>
<th>Start wavelength [nm]</th>
<th>End wavelength [nm]</th>
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<tbody>
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<td>1</td>
<td>403.5</td>
<td>415.6</td>
</tr>
<tr>
<td>2</td>
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<td>5</td>
<td>545.3</td>
<td>554.2</td>
</tr>
<tr>
<td>6</td>
<td>614.5</td>
<td>625.2</td>
</tr>
<tr>
<td>7</td>
<td>659.0</td>
<td>669.8</td>
</tr>
<tr>
<td>8</td>
<td>676.9</td>
<td>684.1</td>
</tr>
<tr>
<td>9</td>
<td>700.2</td>
<td>709.1</td>
</tr>
<tr>
<td>10</td>
<td>750.3</td>
<td>755.7</td>
</tr>
</tbody>
</table>

The CASI data were geometrically corrected and radiometrically calibrated at delivery. These data were then atmospherically corrected by using the 6S-code [5], which compensated for the atmospheric effects and converted the data (representing upwelling radiance at the sensor) into ground reflectance. Thereafter, the mean image was computed for the 10-bands image (fig. 12a), and global thresholding was applied to the mean image to identify and ex-
tract the water-region hyperspectral pixels from the 10-bands image (fig. 12b).

The methodology developed in paper [VI] was applied to this image to extract a number of surface water quality parameters. In paper [V], FVBA was applied where well-defined Feature Vectors or Components were available. On the other hand, in paper IV, FVBA was used for feature extraction and classification.

Figure 11. Map over the region of Norrsundet, Sweden.

Figure 12. (a) The mean 400×400-pixels sub-image covering the area of investigation. (b) The corresponding water-region mask with the marking points P1, P2 and P3 for the passage between the basin and river mouth, the waste-water discharge point into the basin, and the outlet point from the basin to the archipelago.

In paper [V], well-known spectral signatures were found in the literature. Figure 13 shows the estimated absorption spectra of chlorophyll a and b, depicted from [6]. Reflection spectra of three major water types are pre-
sented in Figure 14, depicted from [7]. Approximate absorption spectrum of Dissolved Matter (DM) is shown in Figure 15, depicted from [8].

PCA and ICA were applied to the CASI image according to two approaches: band-wise and spectral-wise, by arranging the data in a matrix so that each band was put as a row or column in the matrix, respectively, and then transforming the data, after normalisation into zero-mean and unit variance data (i.e. whitening).

Fig 13. Absorption spectra of Chl-a and Chl-b. Based on a figure from [6].

Fig 14. Reflection spectra of three major water types: (a) with high phytoplankton and SPM (Suspended Particulate Matter) concentrations, (b) with low phytoplankton but high SPM concentrations, (c,d) with low phytoplankton and SPM concentrations. Based on a figure from [7].

Fig 15. Absorption spectrum of DM. Based on a figure from [8].
The results of PCA and ICA represented pairs of spectral signatures and the corresponding relative weighting maps. The FVBA task was to find linear combinations of these spectral signatures that were as close as possible to those retrieved from the literature. The corresponding weighting maps were then considered as showing the relative concentration maps of those substances in the water. Figure 16 presents some of the results.

On the other hand, according to apriori knowledge, the most probable place to find high concentrations of waste water is at the upper left corner of the basin, and the neighbouring regions, since waste-waters are discharged there. Hence, the FVBA task here is to find linear combinations of the weighting maps to obtain results showing high pixel values at that place in the region. The corresponding spectral signatures will show the spectral characteristics of waste water (figure 17), which are indicated by laboratory measurements of the absorption spectrum of the same waste water (figure 18).

Figure 16. Spectral signatures and the corresponding relative concentration maps (white = maximum) of (a) Chl-a, (b) Chl-b, (c) Chl-a & Chl-b, (d) SPM+DM.
In paper [IV], to be able to perform the FVBA task for feature extraction, field measurements of water quality parameters were required. Also in August 1997, but at another site, namely Lake Erken, located about 180 kilometers south-east of Norrsundet, water samples were collected from 22 sampling stations and analysed in laboratory to measure the concentration of chlorophyll-α and phaeophytine-α (referred to as Chl-α) in these samples. The measured concentrations varied between 2.9 – 50.6 μg/l. A handheld Dual GER 1500 spectroradiometer was used to measure the up- and down-welling radiance above the lake surface at all sampling stations, and finally compute the reflectance spectra at these stations. The measured spectra had 513 spectral bands in the wavelength range 400 – 900 nm.

Fig 17. Waste water concentration maps (white = maximum) and spectral signatures: (a) band-wise ICA, (b) pixel-wise PCA, (c) pixel-wise ICA.

Figure 18. Absorption spectrum of concentrated outlet water. Based on a figure from [9].
These data were used to generate descriptive spectral signatures that could describe the impact of Chl-a on the spectral properties of the water. Two such signatures could be found by performing two different iterative normalisation approaches, as illustrated by figure 19, where spectra were arranged as column or rows in a matrix which was whitened (i.e. converted into zero-mean and unit variance data) and transposed a limited number of times (until a stationary result was reached). More details about these two approaches can be found in the paper.

![Figure 19. Iterative normalisation.](image)

The resulting descriptive spectral signatures were applied to the Norrsundet-image which was also normalised according to those approaches. This resulted in two maps (denoted $a_1$ and $a_2$) describing the correspondence between the data of Norrsundet and Lake Erken, as shown in figure 20. The waters in the region of Norrsundet which have the same quality as Lake Erken, should correspond to high values in both of the correspondence maps. Otherwise, low values are obtained in at least one of the maps.

Figure 21 presents a map generated by classifying the image using the correspondence maps, where class 1 represents pixels corresponding to high $a_1$ values but low $a_2$ values, class 2 corresponds to low values in both maps, class 3 corresponds to low $a_1$ values but high $a_2$ values, and class 4 corresponds to high values in both maps. The mean values of $a_1$ and $a_2$ were used as a threshold to determine if a value was high or low in these maps.

![Figure 20. The correspondence maps: (right) $a_1$, (left) $a_2$ (white = maximum).](image)
Obviously, in figure 21, class 4 represents water unaffected by the waste water, while classes 1, 2 and 3 represent contaminated waters. Comparison with the map of the Norrsundet region in figure 2 results in the conclusion that class-1 waters are mainly found near the waste-water discharge point P2 into the basin, and the outlet P3 point from the basin to the recipient (the archipelago), class-3 waters are found in the basin and also in the river mouth region near the passage between the basin and river mouth (it can be clearly seen how contaminated waters flow southwards through the passage into the river mouth), while class-2 waters are mainly found in the recipient (with coastal seawater) and also observed in the area where a mix between riverine and coastal seawater is found (the sea water injection can be clearly seen, in addition to the sharp boundary where riverine and coastal seawater meet).

Figure 21. Classification result showing four types of water.

The relation of this approach to spectral anomaly detection algorithms was also investigated.

Paper III

Hyperspectral image data has been acquired, by using the Compact Airborne Spectrographic Imager (CASI), over Lake Erken (fig. 22a) in Sweden, during a CASI-campaign in August 1997. At approximately the same time of recording these image data, water samples have been collected (at 22 sampling stations with known coordinates measured by using a dGPS unit) and analysed in laboratory to measure the concentration of chlorophyll-a &
phaeophytine-α (referred to as Chl-a), suspended particulate organic matter, SPOM, suspended particulate inorganic matter, SPIM, and suspended particulate matter, SPM, in these samples. Table 2 presents the ranges of these measured values. A handheld Dual GER 1500 spectroradiometer was used to measure the up- and downwelling radiance above the lake surface at all sampling stations, and finally compute the reflectance spectra at these stations. The measured spectra had 513 spectral bands in the wavelength range 400 – 900 nm.

<table>
<thead>
<tr>
<th>Number of samples</th>
<th>Values-limits</th>
<th>Chl-a &amp; Phaeo-a</th>
<th>SPM</th>
<th>SPOM</th>
<th>SPIM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sampling-stations measurements</td>
<td>Minimum</td>
<td>2.9</td>
<td>1.7</td>
<td>1.3</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>50.6</td>
<td>7.3</td>
<td>6.9</td>
<td>1</td>
</tr>
<tr>
<td>Continuous measurements</td>
<td>Minimum</td>
<td>1.9</td>
<td>1.25</td>
<td>1.2</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Maximum</td>
<td>75.5</td>
<td>11.11</td>
<td>10.3</td>
<td>0.8</td>
</tr>
</tbody>
</table>

In addition to that, a set of 1722 continuous field measurements, of the concentrations of Chl-a, SPM, SPOM and SPIM, were acquired (at about 2-seconds interval) on a boat which scanned almost the whole lake in a zigzag manner, as shown in figure 22 presenting a spatial-mode (fig. 22b) and a spectral-mode (fig. 22c) mosaic-images (generated by merging or putting together spatially-neighbouring CASI-scan lines), with overlaid white continuous-measurements trace and black stars showing the sampling stations. The ranges of the values of these measurements are also listed in table 2. Two spatial-mode images (referred to as Image 1 and Image 2) were acquired (on August 6th and 7th, 1997) to have 14 spectral bands (table 3 presents the band specifications of the CASI spatial-mode) and 850×2650 pixels where each pixel covers 4×4 meters of the lake surface. On the other hand, only one spectral-mode mosaic-image (referred to as Image 3) was obtained having 288 spectral bands (in the approximate wavelength range of 400-900 nm) and 61×110 pixels where each pixel covers about 57×105 meters of the lake surface.

The CASI images were processed in exactly the same way as in the case of the image of Norrsundet (in paper IV) to correct the data and exclude land pixels.

The work in this paper demonstrates the efficiency of using linear statistical modelling for estimation of the concentration of various substances in lake water using the remotely sensed multi- and hyperspectral images to-
gether with the extensive field measurements collected over Lake Erken in Sweden.

A linear relationship was assumed between image data and the corresponding field measurements, and the transformation coefficients were estimated using the least squares method. The resulting coefficients were used to transform new image data into the corresponding substance concentrations. Estimation errors were computed and concentration maps were generated for chlorophyll-a and phaeophytine-a, suspended particulate organic matter, SPOM, suspended particulate inorganic matter, SPIM, as well as total suspended particulate matter, SPM (SPOM+SPIM). Figures 23 shows the concentration maps for the spatial and spectral mode CASI images.

<table>
<thead>
<tr>
<th>Band No</th>
<th>Start wavelength [nm]</th>
<th>End wavelength [nm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>403.5</td>
<td>415.6</td>
</tr>
<tr>
<td>2</td>
<td>436.5</td>
<td>446.9</td>
</tr>
<tr>
<td>3</td>
<td>483.7</td>
<td>494.2</td>
</tr>
<tr>
<td>4</td>
<td>504.8</td>
<td>515.3</td>
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<tr>
<td>5</td>
<td>545.3</td>
<td>554.2</td>
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<td>555.9</td>
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<td>761.1</td>
<td>766.5</td>
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<tr>
<td>13</td>
<td>768.3</td>
<td>780.8</td>
</tr>
<tr>
<td>14</td>
<td>859.9</td>
<td>868.9</td>
</tr>
</tbody>
</table>

Estimated results from all approaches were compared with the corresponding field measurements and common shifts between these values were found. Therefore, simple matching was performed between estimated and measured values, to produce more fair results. The graphs, in the left and right columns of figure 24, show comparisons between estimated and measured values, before and after matching, respectively. Good correlations were obtained between estimated and measured values for Chl-a, SPM, SPOM and SPIM, in all CASI images (including the simulated 14-bands images produced from the spectral mode CASI images).

Descriptive spectral signature pairs (figure 25), describing the impact of Chl-a, SPM, SPOM or SPIM on the spectral characteristics of the water,
were generated, analysed and also used to predict (in the same fashion as in FVBA) the corresponding water quality parameters in image data, with the same estimation accuracy as the linear statistical model.

Figure 22. (a) Map of the research area of Lake Erken, north-east of Stockholm, Sweden. (b) Spatial-mode mosaic-image. (c) Spectral-mode mosaic-image, with overlaid white trace for the continuous measurements and black stars showing the sampling stations’ positions in the lake.
Figure 23. Concentration maps for Chl-a, SPM, SPOM and SPIM in Lake Erken, Sweden. (a) Spatial mode CASI image. (b) Spectral mode CASI image.

In the cases of Chl-a, SPM and SPOM, the descriptive spectral signatures pairs were similar, describing overall increase in reflectance in the wavelength intervals 490-670 nm and 700-735 nm. Also, steeper peaks appear in the wavelength intervals 540-670 nm and 690-845 nm, while deeper troughs can be found in the wavelength intervals 400-530 nm and 670-690 nm. In the case of SPIM, overall reflectance increase can be observed in the wavelength intervals 500-530 nm and 560-690 nm, a deeper trough at wavelengths below 530 nm, and steeper peaks in the wavelength intervals 550-690 nm and 760-775 nm.
Figure 24. Comparison between estimated (thick grey/green) and measured (thin black/blue) surface water quality parameters, (left column) before matching, and (right column) after matching. The parameters of interest are Chl-a, SPM, SPOM and SPIM, for which results are presented on rows 1, 2, 3 and 4, respectively.
Feature vector based analysis (FVBA) was also employed to generate transformation coefficients that could be used to estimate water quality parameters from image data, also, with approximately the same accuracy as the previous methods.

Backward elimination was applied to Image 3 that had 288 spectral bands, in order to find out which of these bands could be excluded and still get the same or maybe better parameter-prediction result, when using the methods presented previously. Two respectively three broad spectral bands were obtained when beginning the elimination from band 1 or band 288, respectively. Figure 26 illustrates these results. This method showed that using a green band and a near infrared band (starting at 813.5 nm) produced the best estimation results for Chl-a, SPM, SPOM and SPIM (cf. figure 26).

Finally, the impact of performing atmospheric correction was investigated, in addition to applying linear statistical modelling for the purpose of combined atmospheric correction and ground reflectance estimation.

The linear statistical method and the approach using descriptive spectral signatures are more computationally efficient than FVBA. Note that the artefacts and shortcomings of the used data decrease the observed performance of the employed methods when processing these data.
Figure 26. The backward elimination results when starting from band 1 (producing broad bands a and d), or band 288 (producing broad bands a, b and c).

The developed approaches can be applied to other remote sensing applications utilising multi- and hyperspectral data acquired by satellite- and airborne systems. Site- and sensor independent statistical method can be achieved if a one-to-one relation can be achieved between field reflectance spectra and the corresponding corrected image spectra, which requires more efficient atmospheric correction and radiometric calibration methods. It is also possible to build a number of statistical models for various waters and use descriptive spectral signatures in a similar fashion as presented in [IV] to be able to identify the most suitable model to be used in each case.

Paper VII

A field experiment was carried out during 1998 in spring wheat crop (*Triticum aestivum*) near Uppsala, Sweden. Within an area of 100×50 m, 0.25 m² circular test areas were randomly selected and used for spectral measurements assessments of disease severity carried out at 17, 27 and 30 July and 10 and 17 August, totally 120 observations. In the disease severity sample, 30 fully developed shots, per observation, were randomly selected in the 0.25 m² test areas and visual assessment of the percentage necrosis of the three top leaves were made. The mean value was calculated including all three leaves on all shots. The field was naturally infected and the predominant fungi pathogen was *Drechslera tritici-repenti* causing the tan spot disease.

Simultaneous hyperspectral reflectance measurements were made, just prior to disease severity sampling process described above, in the test areas in 164 spectral bands in the spectral region 360 to 900 nm using a spectroradiometer. The spectroradiometer recorded irradiance from the sun and nadir
radiance from the crop simultaneously. The sensor was at about 2 m height, which gives a target circular area of about 0.25 m² (with a diameter of about 56 cm). Each date, spectral sampling and collection of shots were completed within a few hours around mid day and the spectral measurements were made when the sun were not shaded by clouds.

Figure 27 shows spectral signatures taken from the used data set with various levels of disease severity, which is proportional to the loss in leaf area, from about 0.6 % and up to about 76.1 %.

The results of this work indicated great potential of using FVBA in combination with a suitable linear transformation such as ICA or PCA, for studying diseased agricultural crops. The required FVBA task in this case was to perform feature extraction (using training data), then classify new hyperspectral crop reflectance data. However, it has been noticed that the most important step here was to first pre-process (i.e. to whiten or normalise) the data efficiently to be able to reveal and magnify the ‘hidden’ differences between the data samples which represent different plant conditions to improve the performance of the method. In addition to that, in the training data set, the hyperspectral reflectance vectors were sorted with respect to the corresponding field leaf-damage measurements to ease the search for appropriate linear combinations. Then, a linear transformation (PCA or ICA) followed by the FVBA-task was performed to get a spectral signature which describes the changes in the spectral properties of the plants when the disease severity was increased. A genetic optimisation algorithm was used to generate this spectral signature by taking linear combinations of the pairs produced in the training phase, since the used transformations were linear. Finally, the resulting spectral signature was used to classify new hyperspectral data.

![Figure 27. Hyperspectral crop reflectance data samples.](image-url)
It was also noticed that different normalisation approaches produced different spectral signatures. The spectral profile in Fig. 28b (the ‘band-wise+spectral’ approach) could partly be interpreted as an effect of increased photosynthetic productivity, as it is very similar to a classical vegetation reflectance spectrum with low absorption around 550nm and above the red edge, at 750nm. This spectral profile indicates an overall flattening of the reflectance spectra for high levels of disease severity. The other spectral profile, in Fig. 28a (the ‘spectral+bandwise’ approach), has differing characteristics. The low weights in the near infrared bands between 750 and 830nm indicate a decline of the shoulder of the near infrared reflectance plateau for high levels of disease severity. In the visible range there are high weights from 550 to 750nm that correspond to sensitivity to a general decrease in absorption.

The correlation between the resulting spectral signature and new hyperspectral data can be considered as being proportional to disease severity in the crop. High correlation is indicated between the resulting estimates and the corresponding field measurements of disease severity. Figure 29 presents the classification results. These results underline the usefulness and efficiency of using this non-destructive remote sensing technique not only to discriminate between healthy and diseased plants, but also to determine disease severity levels.

![Figure 28. Descriptive spectral signatures when using: (a) the ‘spectral + band-wise’ normalisation approach; (b) the ‘band-wise + spectral’ approach.](image)

However, representative pairs of field measurements of disease severity and the corresponding hyperspectral reflectance data vectors are required to build a suitable (relatively small) training data set that can be used in the training phase of the method to produce the specific spectral signature which can be used later, in the classification phase, to study new hyperspectral data of the same crop suffering from the same pathological condition. Hence, such a training set is required for each type of crop, to enable the specific spectral signature to be obtained for the diseased or stressed crop.
Papers VIII and IX

For the work in paper [IX] additional data were collected from a barley field (*Hördeum distichon*), near Uppsala, Sweden, in 2003. Reflectance measurements and above ground plant mass (fresh weight) were collected on 10 sample spots 23 June, 15 spots 25 June and 10 spots 26 June 2003 within a field trial area of 40×20 m. The total number of observations was 823. At each sample spot, a thinning procedure was used where about half of the standing shoots were evenly selected and cut at ground level within a 0.88 m² area between the reflectance measurements. In the last cut, all remaining shoots were removed from the sample area.

In this manner hyperspectral reflectance and corresponding plant mass from each sample spot were recorded in four levels ranging from 100 % plant coverage to 100 % bare soil exposure. The crop was at stem elongation development stage (before booting stage). Spectral measurements were made during both sun lit and overcast sky conditions. At 23 and 26 June varying amounts of crop residue from a preceding wheat crop, collected from a nearby field, were spread on the ground in order to introduce variations to the ground reflectance. Figure 30 shows five hyperspectral data samples with varying plant densities.
In these papers, a new approach was used to characterise and estimate disease severity and plant density. Here, the linear transformation step was skipped and the normalised data (using combinations of spectral- and band-wise normalisations) were compared with reference data (also normalised) using a nearest neighbour approach. Descriptive spectral signatures were computed using a linear transformation model. The results of the disease severity and plant density cases are shown in figures 31 and 32, respectively.
Figure 32. The results of the plant density case study when starting by band-wise (left) and spectral (right) normalisation in the pre-processing step.

The observation that can be clearly noticed when comparing the descriptive spectral signatures is that the general profiles of these signatures are mirrored up-side down, which is reasonable as increased disease severity causes decreased plant density.

High correlations were obtained between the classification results and the corresponding field measurements confirming the efficiency and usefulness of this approach. The major advantage of this approach is its simplicity and low computational load, which makes it suitable for real-time on-vehicle applications. It is potentially fast, sensitive, non-destructive and can operate in the field without the need for any sample preparation - all the requirements of an ideal stress detector.
Weighted neural networks for image data reduction and segmentation

Segmentation becomes a difficult task as the dimensionality of the data increases, due to the sparse structure of such data. However, segmenting high-dimensional data, e.g. hyperspectral images, is crucial to be able to simplify the analysis of the data by focusing on a certain part of it or on data samples of the same or at least “nearby” spectral properties.

It has been shown in the literature through numerous research works that, usually, fuzzy clustering algorithms [10 - 14] perform better on high-dimensional real-world data than crisp clustering methods. Artificial Neural Networks (ANN) [15] have many advantages that can fully be utilised if a suitable combination, of a flexible network-structure and an efficient adaptive learning-mechanism, is used in designing the ANN. Therefore, the goal here is to construct a fuzzy clustering method using an efficient neural network to make use of these advantages. See [16 - 18] for such efficient combinations, which are usually called Neuro-Fuzzy Systems.

The aim here was to construct such a system that succeeds in processing high dimensional data. The developed algorithms and results were published in the papers [X – XIV].

Paper X

A Weighted Fixed Neural Network (WFNN) was introduced and discussed in this paper. The basic idea of the WFNN algorithm was based on the famous Hebb’s postulate [21] stating that the connection between two winning neurons gets stronger. Hence, the aim was to generate a weighted graph, consisting of weighted nodes connected by weighted edges, reflecting the topology of the input data set. “Heavier” nodes and “stronger” connections, in the resulting weighted graph, corresponded to denser regions in input space.

Given an input data set \((\mathbf{eR}^k)\), an initial \(k\)-dimensional equally spaced zero-weighted grid is generated. The data set was mapped to the grid by assigning to each node a weight corresponding to the portion of input data samples that were the nearest to it. The \(n\) nearest nodes to each data sample (i.e. the “winners”) were considered. Connections between the 1st “winner”
and each of the other $n-1$ “winners” were established and weights were assigned to them as in the case of the nodes.

Figure 33. Clustering performed on synthetic data sets with clusters at the same level: (a) input data set, (b) the resulting sub-nets (task 2), (c) clustered data (task 3).

The fuzziness of the system could be chosen by determining the number of nodes in the net, as well as the number, $n$, of the nodes (the “winners”) that could be connected when processing an input data sample \textit{(a signal)}.

The weighted graph is obtained by deleting all zero-weighted nodes from the grid. Note that, no zero-weighted edges exist. In addition to that, the resulting net doesn’t always have a grid structure.
But, this “preliminary” WFNN algorithm suffered from some practical limitations making this algorithm not suitable for processing large data sets of high dimensions, due to the high memory and computational load. Some improvements were added to the algorithm to overcome these limitations.

Then a fuzzy clustering algorithm based on WFNN (FC-WFNN) was constructed as follows:

1. Building up a weighted net by processing the input data set, using the WFNN algorithm.

2. Clustering the resulting weighted graph, using a watershed-like procedure.

3. Clustering input data, by mapping the clustered net onto the input data set, using a nearest neighbour classifier.

Finally, the method was evaluated using synthetic as well as real world data. The results showed that the WFNN failed in adapting perfectly for data of high dimension.

Figure 33 shows some clustering examples performed on synthetic data sets.

Paper XI

A modified version of the incremental neural network using the Growing Neural Gas (GNG) algorithm [19], referred to as the Weighted Incremental Neural Network (WINN), was introduced to be used in the first step of the proposed clustering algorithm, referred to as FC-WINN (Fuzzy Clustering using WINN). WINN is an incremental (i.e., growing) self-organising model [20], with no pre-defined structure, and therefore no restrictions on the dimensionality of the input data to be processed.

The model is built-up by successive addition, adaptation, and sometimes deletion of elements, according to suitable strategies, until a stopping criterion is met. The goal is to efficiently build-up a model that reflects the original distribution of the input data set. And if the data set has different local dimensionalities in different parts of input space; e.g. if some of the data samples lie on a one-dimensional line, while some others lie in a two-dimensional plane, and the rest of the samples are arranged as a filled three-dimensional cube, then when using this WINN algorithm there will not be any kind of wastefulness with the resulting representation of this data set, because net-elements are generated and used exactly when and where needed.
The new WINN algorithm produces a weighted graph, consisting of weighted nodes connected by weighted edges. The weights are proportional to the local densities of the data samples in input space. This results in a net that preserves the topology of the input data set. The number of the resulting nodes is usually much less than the number of the input data samples, which leads to a considerable data reduction for the problem at hand.

The basic idea of the WINN algorithm is to generate and distribute a number of weighted nodes connected by weighted edges in the input data space, so that a relatively high weight-value corresponds to a relatively high density of input data samples in a neighbourhood around the corresponding node or edge, and vice versa. The algorithm begins with only two nodes connected by an edge, then new nodes and edges are generated and the old ones are updated (and sometimes deleted), while the learning process proceeds, until a stopping criterion is met.

A fuzziness factor is introduced in the resulting weighted graph (which is our model here), by propagating the influence of the input signal (which is the input data sample that is currently presented to the neural network) to the \( n \) nearest nodes in the net (i.e. the \( n \) winner nodes or the “winners”), by updating them according to the signal-value, and by establishing and updating edges between the first “winner”, which is the nearest node to the signal (i.e. the best match), and the other \( n-1 \) “winners”. The higher \( n \)-value is chosen, the higher connectedness of the resulting net is obtained, and consequently the fuzzier the system becomes. A fuzzy system is obtained since we have \( n \) edges that are affected by each input signal, which fuzzyfies the relations between the nodes. Obviously, a higher fuzziness-level corresponds to a lower resolution-level for the system. The reason is that a higher \( n \)-value strengthens the connections between the nodes, which reduces both the within- and between-clusters distances. Consequently, nearby clusters are merged together when the \( n \)-value is increased. At last, when \( n \) is too high, a single cluster is obtained including the whole input data set.

Another factor that affects the fuzziness of the system is the number of nodes in the resulting net, which is proportional to the resolution-level of the system. Choosing a denser net, i.e. consisting of more nodes, produces more and consequently smaller clusters; i.e. more details can be captured and revealed.

Hence, it can be stated here that the number of the resulting clusters is mainly determined by the choice of the number of nodes and the \( n \)-value for the WINN algorithm. Furthermore, the resulting clusters can be of arbitrary distributions (having arbitrary shapes, densities and sizes), depending on the distribution of the input data set.

What is new with WINN, when considering fuzzy systems, is that there is no need to explicitly define any fuzzy membership function, e.g. a Gaussian or a triangular function. The resulting weighted net functions as a fuzzy representation of the input data set. While in all other existing fuzzy systems
(e.g. [10 - 14]), including statistical as well as neural networks approaches, a fuzzy membership function must be defined to be used to cluster and classify input data. The WINN algorithm overcomes the disadvantages of the previous WFNN algorithm [X], when processing high-dimensional data.

Figure 34. Clustering performed on synthetic data sets: (a) input data, (b) the resulting weighted connected net from task 1, (c) the resulting sub-nets from task 2, (d) clustered data (task 3). Where different clusters/sub-nets are denoted by different markers (*, o, Δ, △, V, etc) as well as different grey-scale colours.
The FC-WINN fuzzy clustering algorithm is a three-tasks algorithm and has the same structure as the FC-WFNN algorithm. Figure 34 shows clustering results performed on synthetic data sets.

The FC-WINN was applied to different data sets of various dimensionalities to showed superior performance. Finally, the fuzziness of the model was discussed and explained.

Paper XII

This paper provided a brief presentation of WFNN and WINN as well as their clustering algorithms, then compared their behaviour and performance, and showed the advantages and superiority of WINN and its clustering algorithm (FC-WINN).

The predefined fixed positions of the nodes make the adaptation mechanism of the WFNN algorithm unusually poor. This was observed in the case of the 9-dimensional Glass database (table 4), where the algorithm failed in adapting perfectly. On the other hand, using the WINN algorithm could offer more flexibility than the WFNN algorithm, when working with high-dimensional data sets of “complex” distributions. The reason is the incremental behaviour of the WINN algorithm, that new nodes are generated and placed when and where they are exactly needed, generating a net that reflects the data distribution in input space; i.e. denser parts of the resulting net correspond to denser regions in input data space.

Three databases were selected: the Fisher’s Iris database, the B.German’s Glass Identification database, and the James Cook University Thyroid gland database, which are composed of 150 4-D patterns (∈3 classes), 214 9-D patterns (∈2 classes, window or non-window glass), and 215 5-D patterns (∈3 classes), respectively. The classification rate is calculated as the percentage of patterns which are correctly placed into clusters. Table 4 reports a comparison between the best results of the WNN-based algorithms and the results reported in [22] for using the standard fuzzy c-means (FCM) algorithm and the real-coded genetic algorithm (RCGA). The Euclidean norm was considered in the three clustering algorithms.

<table>
<thead>
<tr>
<th>Database</th>
<th>Classification Rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>WINN</td>
</tr>
<tr>
<td>Iris</td>
<td>96.00</td>
</tr>
<tr>
<td>Glass</td>
<td>95.79</td>
</tr>
<tr>
<td>Thyroid</td>
<td>91.16</td>
</tr>
</tbody>
</table>
Paper XIII

This paper addressed the use of the WINN and FC-WINN algorithms for hyperspectral image segmentation and data reduction.

Figure 35. The segmentation result for the hyperspectral image of Lake Erken (1400 nodes, n=2, 5 clusters).

Figure 36. The segmentation results for the cells hyperspectral image (900 nodes, n=2, 8 clusters).
Figures 35 and 36 show the segmentation results for the Lake Erken and the cells hyperspectral images, respectively. Visual inspection and comparison between the segmentation results and the corresponding original images, underline the meaningfulness of the results, as well as the usefulness and efficiency of this technique for segmenting this type of high-dimensional image data.

In the case of the Lake Erken, the segmentation result (when considering the big or coarse details, and only the water-regions pixels are taken into account) is similar to other results obtained by means of using linear regression with field measurements.

In the case of the prostate-cancer-cells hyperspectral image, the segmentation results show the ability of segmenting different parts of the cells (or different types of tissues), indicating that they have different spectral properties. And this algorithm succeeds in separating different parts in the cells (or different types of tissues) in different clusters. For instance, the nuclei (which are layers of epithelium cells nuclei) can be clearly recognised as the dark grey (magenta) regions in the resulting image. The nuclear sizes can be used as a discriminative feature to assess the degree of malignancy in prostate cancer; the larger this area is, the more likely there is cancer.

![Figure 37. Histograms for the segmentation results in Figure 35: (a) for the segmented image, (b) for the resulting sub-nets.](image)

Figures 37 and 38 show histograms for the segmentation results in Figures 35 and 36, respectively. Comparisons, between the histograms of the segmentation-result images and the corresponding histograms for the resulting sub-nets, show that the relative size of a resulting sub-net is not always proportional to the relative proportion of underlying (hyperspectral) pixels in input space. The reason is that a denser region can be presented by relatively few nodes when using this method. Consequently, intensive dimension reduction is obtained. This can easily be seen by comparing the number of the nodes in the resulting weighted graph, with the number of the (hyperspec-
tral) pixels in the original image. For instance, we have \((1,400 \text{ nodes})/(1,277,540 \text{ pixels}) < 0.11\% \) and \((900 \text{ nodes})/(512 \times 512 \text{ pixels}) < 0.35\% \) in the case of the Lake Erken and the cells images, respectively.

Figure 38. Histograms for the segmentation results in Figure 36: (a) for the segmented image, (b) for the resulting sub-nets.

Paper XIV

This little paper compared the FC-WINN to PRECLUST which was based on the classical ISODATA algorithm, when segmenting colour-infrared aerial photos. The most striking difference between the two methods was that FC-WINN managed to reduce the number of classes to two-thirds of what PRECLUST needed. Moreover, FC-WINN created much more uniform and less noisy segments (e.g. the whole road network in the image ends in one segment) than PRECLUST, which was most successful in discerning foreground from background, while FC-WINN was more successful in all other aspects.
Conclusions and future research

The work in this thesis covers hyperspectral image generation (utilising multiple filter mosaics), processing (using weighted incremental neural networks) and analysis (using linear statistical methods). It is essential to have a low-cost and user-friendly instantaneous hyperspectral imaging instrument, in addition to automatic processing and analysis algorithms for information extraction and interpretation of the images.

Future research should focus on further development of the camera spectrometer concept to achieve better performance and produce a ready to use imaging instrument, in addition to constructing a general self-organising and learning system that can be adapted for various applications, such as environmental monitoring, biological, earth science, transportation, precision agriculture, and forestry applications.

The small size of the initially acquired single image (which is as small as a monochromatic image) makes this approach useful for applications where the images are transferred on-line to distant places to be saved and/or processed. Note that a camera spectrometer can be used for both remote (i.e. far from the target object) and near-to-target sensing, providing instantaneous images containing both spatial and spectral information.

One important issue, regarding the camera spectrometer, is to take care of mixed pixel effects found when the constituting colour mosaics are not perfectly aligned, e.g. when putting these mosaics in the optical path, not directly attached to the imaging sensor array, as illustrated in paper II. Exact alignment can certainly be obtained when integrating these mosaics with the imaging sensor array. The spectral resolution of the system depends on the quality and performance of the used mosaic filters, in addition to appropriate training of the system (requires the use of a representative training data set in addition to employing an efficient training algorithm) to be able to convert multiple filter responses into spectra of desired quality.

Regarding the applications where hyperspectral data analysis is desired, laboratory and/or field measurements including spectral reflectance measurements and the corresponding conventional assessments or measurements of the parameters of interest (e.g. surface water quality parameters) are required for all interesting cases, to be able to build a data-base of reference data that can be used to generate descriptive spectral signatures to be used to determine the appropriateness of new data regarding each case in the database, and to consequently, identify the most likely case the new data belong
to. Thereafter, quantification of appropriate parameters (depending on the identified and selected case from the data-base) is performed. This will establish efficient site- and sensor-independent analysis.

On the other hand, regarding the WINN applications, there is still need for development of efficient graph matching methods - inexact matching is desired since real-life target objects never look exactly the same when observed at different times. Also, better segmentation algorithms, than the currently used FC-WINN algorithm, are required.

Finally, cooperation between the WINN technique and the statistical analysis methods can yield what can be called conscious (remote or near-to-target) sensing systems, where spatial information are extracted by WINN while spectral characteristics are retrieved by statistical assessment. Note that appropriate spatial and spectral resolutions are required.
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