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Interactive Explorative Analysis of Multivariate Images Using Principal Components

BY

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Abstract

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Images showing exactly the same scene, acquired for example at different points in time or by using different wavelength bands, are traditionally segmented into problem-specific regions using multivariate statistical methods running in batch mode. Today, the computational power of general workstations is sufficient for providing an interactive environment for analysis of multivariate image data.

A software for interactive explorative multivariate image analysis utilizing principal component analysis has been designed and implemented. It is evaluated using four application examples from medicine and remote sensing. The applications display different noise amplitudes and distributions.

An existing methodology for interactive explorative multivariate image analysis has been extended with basic image modeling, visualization tool for the high-dimensional feature space, and preprocessing of the analysed multivariate image data. With these extensions, the methodology can be used in an iterative manner.

Interactive explorative analysis of the application examples using the developed methodology results in suggestions for preprocessing of the noise. Both additive noise and signal dependent noise can be handled.

The extended methodology can be used for a larger class of images, because it can handle also images with large noise.

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To Maria, Harald
and Thor

This thesis is based on the following papers, which will be referred to in the text by the capital letters A-G.

A. E. Bengtsson, B. Nordin and F. Pedersen,
MUSE - a new tool for interactive image analysis and segmentation based on multivariate statistics,
accepted for publication in Computer Methods and Programs in Biomedicine.

B. F. Pedersen, E. Bengtsson and D. Jonsson,
A numerically derived method for preprocessing of noisy data before applying principal component analysis,
Proceedings of The 8th Scandinavian Conference on Image Analysis, Tromsø, Norway, pp. 981-988, 1993.

C. F. Pedersen, E. Bengtsson and B. Nordin,
An extended strategy for exploratory multivariate image analysis including noise considerations,
submitted to Journal of Chemometrics.

D. F. Pedersen, M. Bergström, E. Bengtsson and E. Maripuu,
Principal component analysis of dynamic PET and gamma camera images: A methodology to visualize the signals in the presence of large noise,
Conference record of the 1993 Nuclear Science Symposium and Medical Imaging Conference, San Francisco, 1993.
The present paper is an extended version submitted to a conference issue of the IEEE Transactions on Nuclear Science.

E. F. Pedersen, M. Bergström, E. Bengtsson, B. Långström,
Principal component analysis of dynamic positron emission tomography images,
submitted to European Journal of Nuclear Medicine.

F. F. Pedersen, E. Bengtsson, T. Hindmarsh, B. Nordell and H. Forssberg,
Using principal component analysis to visualize the spatial distribution of functional areas of the brain as studied with MRI during motor and sensory activation,
Physiology and Function from Multidimensional Images, Proceedings SPIE 2168, 1994.

G. F. Pedersen, L. Andersson and E. Bengtsson,
Supervising a principal component analysis with respect to imagery and application characteristics,
submitted to Photogrammetric Engineering and Remote Sensing.

In the majority of these papers, I did the analysis and compiled the results. My specific contributions to the papers are:

Paper A: Design of the interaction concerning principal component analysis (PCA). The major part of the visualizations used for evaluation of the PCA. Presenting preliminary results for PCA applied to PET images.

Paper B: The major part of the design of the numerical experiments. The evaluation of the results.

Paper C: The major part of the design of a model for extended MIA. The creation of new visualization tools. Modeling of the synthetic data. Analysis of the PET image data.

Paper D: A significant part of the design and modeling of the synthetic gamma camera data. The evaluation of the results.

Paper E: A significant part of the design and modeling of the synthetic PET data.

Paper F: The major part of the analysis.

Paper G: The major parts of the image modeling and the analysis.

Preface

The scientific work presented in this thesis was carried out at the Centre for Image Analysis at Uppsala University. The centre was created in 1988, and it is to a large extent the result of ideas shared by Prof. Ewert Bengtsson and Dr. Tommy Lindell. I congratulate both of you to your achievements, and I thank you for the opportunity to work in this expanding field.

Prof. Bengtsson was my supervisor throughout this work, and I am very grateful for his experienced guidance and encouragement. My assistant supervisors Dr. Bo Nordin, Dr. Mats Bergström, and Dr. Dag Jonsson generously sharing their time and knowledge.

I wish to thank Dr. Paul Geladi at the Research Group for Chemometrics, Umeå University, for supporting me with literature and good advice at numerous occasions.

This multi-disciplinary work would not have been possible without good contacts with a number of institutions. I am grateful to co-authors and collaborators at the Department of Diagnostic Radiology, the PET-centre, and the Department of Mathematics at Uppsala University, the Department of Hospital Physics at the University Hospital, as well as my co-authors at Karolinska Hospital in Stockholm.

I thank my colleagues for creating a working environment which has been most stimulating. Especially, I would like to thank Bosse for writing a lot of useful code, Thomas for being a great travel companion, Håkan for fruitful discussions, and the other members of our special team; Lennart and Dr. Curre.

I thank Ewert, Ingela, Bosse, Håkan, and Johan for helping me with proofreading and other matters when preparing the manuscript.

Each year I was responsible for a Computer Graphics course at the Department of Scientific Computing. Teaching was fun, with friendly and humorous colleagues.

This last month Maria and little Harald did not see too much of me. Still, they supported me in all possible ways. Kärleken övervinner allt.

Finally, I would like to thank the Swedish National Board for Technical Development for financial support.

Uppsala, April 1994

Finn Pedersen

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1 Background

Images are commonly used in science for the visualization of physical objects, processes, simulation results etc. There is a large span in what the intensity value in a picture element (pixel) can represent, depending on the imaging technology. The image scale can for instance vary from the visualization of microscopic objects using electron microscopy, up to the macroscopic world, like the earth imaged from a satellite or the Milky Way through a telescope.

In many disciplines it is possible to acquire several images of exactly the same scene, but with different imaging parameters. The difference between the images could, for example, be that the images were acquired at different points in time (multitemporal), using different spectral wavelength bands (multispectral), or with different acquisition parameters for a medical tomograph. There is no standard term to denote this class of image data. The term multichannel image is associated with remote sensing and multispectral imaging. The terms multi-image and multiband image are too wide definitions. They include for example changing the view of the scene [12]. Therefore, the term *multivariate image* will be used to denote this kind of image data. A multivariate image consists of several bands (images) with a one-to-one correspondence in position.

The motivation for acquiring multivariate image data can be demonstrated by analogy with photographs. A black-and-white photo is a single (univariate) image showing the reflected light over a wide wavelength band, but a colour photo is a multivariate image showing the reflected light in the red, green, and blue wavelength bands simultaneously. A more complete description of the imaged scene is available.

When using this technique, the sensors can be tailored for specific wavelengths and purposes. The multivariate image shows measurements of different variables in the different bands. The bands can of course be viewed as univariate images. A colour image stored digitally in a computer can be displayed on the computer screen as three univariate images, one for each wavelength band.

The acquired image data can be visualized in many ways. A multitemporal image can be shown as a sequence of images. Multispectral images can be shown as pseudo colour images by letting three bands form a colour image. Images from tomographs are traditionally inspected on light boards or on computer screens, image by image, using a grey scale or a colour scale.

The purpose of an analysis could be to quantitate features of specific regions or to identify objects in the scene. This usually requires that the scene is segmented, meaning that the scene is divided into one or more problem related regions. The task of image segmentation is critical, because the results derived will depend upon how successful it was. The segmentation can be done manually by the application specialist, who outlines the interesting areas. Performing semi-automatic or automatic segmentation is very exploratory in nature since there is no general theory, and there are several techniques to choose from [11]. Classification followed by a relaxation step can be used for image segmentation. A classifier first labels the pixels as belonging to one of several classes. Then, the labeling of the pixels is updated until a consistent global interpretation of the image data is achieved. The classification is usually performed in conjunction with different kinds of preprocessing, in order to enhance discriminating features in the scene.

When classifying univariate images, the pixels can be classified using for example texture or thresholding of the grey levels. In the case of multivariate images, multivariate statistical methods are available. Multivariate statistical methods are computer intensive, especially when applied on image data, since the data set is much larger than what is usually the case. An image of size 128 pixels in square, a modest size for images, contains 16384 samples. In order to get a sample size of statistical significance, around a hundred samples are sufficient. Previously, classification using multivariate methods of image data was batch-oriented. This meant that the user fed the algorithms with the necessary data, and then went for a coffee, or lunch, break. When returning, the results were hopefully ready for inspection.

Classification utilizing multivariate statistical methods is traditionally based on access to "ground truth", a term meaning that observations and/or measurements have been made in the imaged region. It is then possible to use the ground truth data to train a classifier, for example a maximum likelihood (ML) classifier, and on a statistical basis classify the pixels in the image. By supplying knowledge, in this case statistics from the training areas, the user makes the classification supervised.

An increasingly important issue for the computer area is the user interaction. Working in a batch-oriented mode in principle only demands a stored file with data and instructions. If interactive software tools are available, the user can preprocess the input data, modify the training areas, or even change classification method if necessary, and have the results displayed immediately. This way of working has a clear advantage over the batch-oriented mode. It lets the user interact with application-specific knowledge, giving an opportunity to acquire more knowledge about the data set, and to improve the understanding of the used methods. Research in human interaction with computers have lately exploded, because the computational power is now sufficient for real-time interaction. For the analysis of multivariate images, this means that the computational power is sufficient for advanced multivariate statistical methods and user interaction.

1.1 Scope of the thesis

I can see three important reasons for performing preprocessing of multivariate imagery. First, it is possible to incorporate interaction in the preprocessing, letting the user interactively supervise the preprocessing by using the human visual system combined with application-specific knowledge. Second, it is possible to reduce the dimensionality of the multivariate image through preprocessing. Third and last, preprocessing is essential for feature enhancement.

Principal component analysis (PCA) is a multivariate statistical method which can be used for these three purposes. It is possible to incorporate user interaction by performing PCA iteratively. This requires that visualizations of the result of a PCA are available, and that the user can perform different kinds of manipulations of the image data set based on conclusions from the visualizations. A successful PCA will reduce the dimensionality of the data set. The first few principal component (PC) images contain the major part of the total variance, and by retaining only these images, the dimensionality of the data set is decreased. The retained images represent dimensions which to a large extent contain the relevant signals, and this can enhance these features in the image.

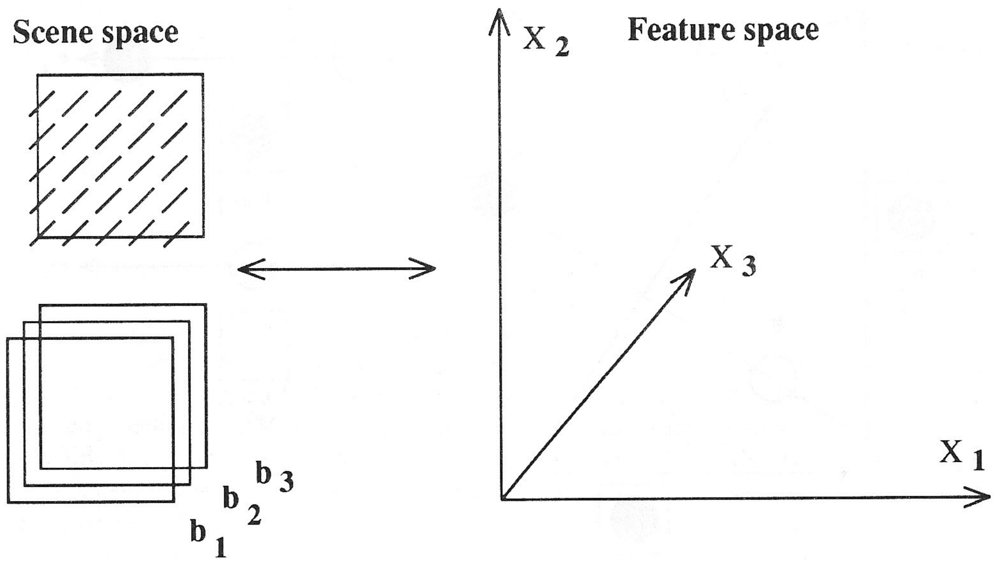

Figure 1: The pixels in a multivariate image can be viewed as pixel vectors in scene space. In this figure each vector contains three elements. The image $\mathbf{b}_i$ is a visualization over a spatial area of the measured variable X_i. The variables span a feature space, and each pixel vector defines a position in this space.

The present work was aimed at creating and evaluating an interactive exploratory software utilizing PCA for preprocessing of multivariate imagery. Special attention was given to the user interaction. The evaluation was done by applying the developed methodology on four application examples from medical imaging and remote sensing.

2 Introduction

In this section the tools and techniques used in the thesis are described. A brief review of related work is also done.

2.1 Scene space and feature space

Using multivariate statistical methods in image analysis means using two spaces. The scene space consists of the samples (pixels) ordered in a matrix, and the appearance of the image depends on the distribution of the grey values. However, consider reordering the samples in some random order. The image would still consist of exactly the same samples, but the scene would change, and maybe not appear meaningful.

From a statistical point of view, the data has not changed, because statistical calculations are done in what will be called the feature space. The feature space is spanned by the measured variables, i.e. the position of the sample is in this space defined by the grey level values in the different bands. An instructive way to view the data set is as an image consisting of p-dimensional pixel vectors. A pixel vector has a spatial position in scene space, but also a position in the p-dimensional feature space, see Figure 1.

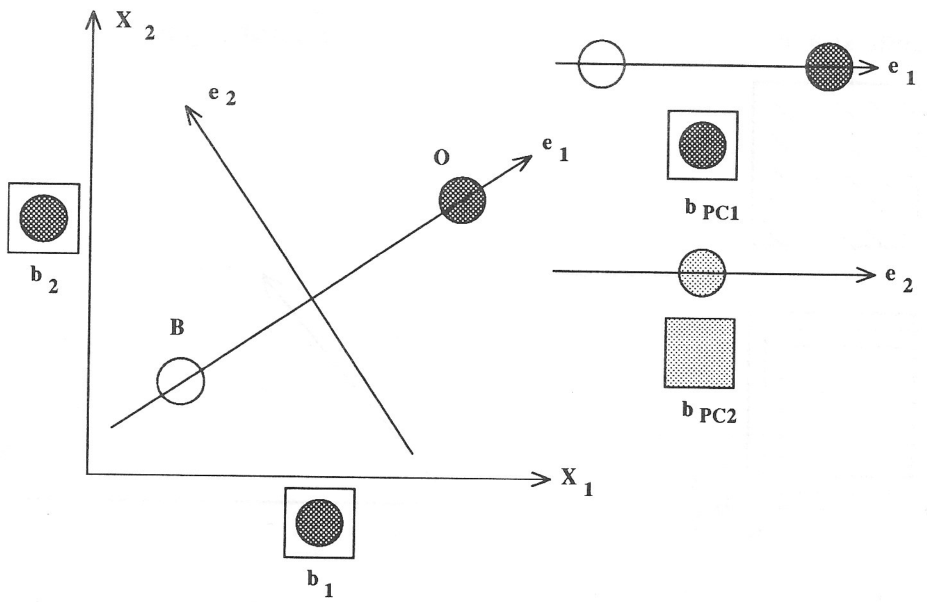

Figure 2: PCA is performed in feature space, and results in a new coordinate system defined by the eigenvectors of the covariance matrix. They represent orthogonal maximum variance directions for the data set.

2.2 Principal component analysis

Principal component analysis is a well established technique used for analysing the variance-covariance structure of a multivariate data set. It is used in many areas, and it is also known under several names. The Hotelling transform, the discrete Karhunen-Loève transform and the eigenvector transform are all synonyms for the PC transform obtained through a PCA [9].

A PCA starts with the calculation of the covariance matrix for the samples, which in the case of multivariate images is the covariance matrix for the bands. The correlation matrix is used when appropriate. The eigenvalues and the eigenvectors are obtained for the matrix. The eigenvectors represent a new base in feature space, and the eigenvalues represent the variance in the direction of the corresponding eigenvector. The complete theory for PCA is described elsewhere [14] [15] [16]. The algorithms used for performing PCA of image data is well described in [8]. The result of a PCA of a p-variate image is a new p-variate image consisting of p PC images, or score images, which describe the covariance structure of the data set more parsimoniously. No information will be lost by changing the coordinate system, because the PC transformation preserves the total variance. In a later step, the number of relevant PC images can be decided, and then the series of PC images is truncated in order to reduce the dimensionality.

Figure 2 shows what happens in feature space. A multivariate image has two bands $\mathbf{b}_1$ and $\mathbf{b}_2$ describing two variables X_1 and X_2 with the same additive normally distributed noise. The figure shows the two bands beside their respective axis in a scatter plot. Both bands show the object O on a background B, and these clusters are identified in the scatter plot. The clusters appear as round blobs due to the noise. A PCA suggests a new rotated coordinate system defined by the eigenvectors $\mathbf{e}_1$ and $\mathbf{e}_2$. $\mathbf{e}_1$ defines the direction in feature space which spans the maximum variance, and this is a direction spanned by the centres of gravity for the two clusters. The second eigenvector $\mathbf{e}_2$ spans a maximum variance direction orthogonal to $\mathbf{e}_1$.

The connection between the scatter plot and the bands $\mathbf{b}_1$ and $\mathbf{b}_2$ is the histograms. Orthogonal projection of the samples in feature space (clusters B and O) upon X_1 gives the histogram for $\mathbf{b}_1$, and similarly for X_2 and $\mathbf{b}_2$. The same procedure can be performed for the new basis vectors defined by $\mathbf{e}_1$ and $\mathbf{e}_2$, giving the histograms for $\mathbf{b}_{PC1}$ and $\mathbf{b}_{PC2}$. To the right in the figure the new PC images are shown under their respective "histograms". In this case it is possible to reduce the dimensionality from two to one, since the first PC image shows the signals, and the second PC image only show noise. This is clear from the feature space representation, and from the "histograms".

Using PCA for preprocessing of image data can be motivated by a number of reasons. It is used in many scientific disciplines as a preparation for factor analysis, regression analysis, or classification schemes. Also, the response time on a general workstation for image data of normal size allows truly interactive work. PCA is included in many statistical softwares, and supporting PCA of images is especially popular in software for remote sensing applications.

2.3 A platform for multivariate segmentation, MUSE

The software used for the work presented in this thesis is part of a larger program system intended as an experimental platform for **MU**ltivariate image **SE**gmentation problems, named MUSE. MUSE was implemented side-by-side with an existing software, EGO, which is used for image handling, filtering, and other low-level image processing routines. The implementation was done on a dedicated workstation IMTEC EPSILON, equipped with a special purpose image processor [1]. This special hardwares performance was sufficient for the short execution times required for truly interactive work.

MUSE supports three main functionalities: inspection of the data in scene and feature space, editing regions of interest (ROIs), and transformations of the data. The general idea is that when a multivariate image is classified and segmented into regions, it should be possible to compare the result with other classification/segmentation schemes. This opens a door for collecting experience on what kind of image data is suitable for which classification/segmentation scheme.

PCA is one of the transformations available, so image preprocessing utilizing PCA is one of the possible ways of starting a segmentation.

2.4 Multivariate image analysis, MIA

In [7] a general strategy is outlined which can be used for supervised classification of multivariate images. It is based on PCA and on user interaction. This is an excellent way of letting the user explore the multivariate data set in scene space and in feature space. By supporting visualization of the transformation and painting in the scene space and feature space views of the data set, the user's application-specific knowledge is incorporated into the process of classification. All the software tools and transformations necessary to carry out MIA were incorporated in the software used for this project from the very start. It was natural to use MIA as a starting point for the work described in this thesis.

2.5 Related work

In the research area of statistical graphics, much progress have been made concerning interactive visualization which will become, or already has become, feasible for data sets as large as image data sets [4] [3]. One way of visualizing a p-variate feature space is by showing subspaces. A 2D or a 3D subspace of feature space showing the samples is called a scatter plot. Using a number of different scatter plots makes it possible to view several dimensions simultaneously. Scatter plot brushing is used to link one object in one plot to the same object in another plot. A generalization is painting multiple views. In this case objects are painted (outlined) and high-lighted in other views of the data. To the best of my knowledge the first presented work on linking scene space to feature space by painting was done in the research area of chemometrics [7].

Another strategy of linking views is to use motion. This could for example be the projection of a rotating 3D scatter plot on a plane. A generalization of this is the Grand Tour, which lets a plane move in the high dimensional space and shows the samples projected onto this subspace [13]. Such techniques have not been used in this work, but they clearly represent a complementary approach for visualization of the data.

3 Applications

The developed methodology has been applied to images from several application fields. These are briefly described in this section for reference.

3.1 Positron emission tomography, PET

PET is used for measuring the concentration of positron emitting radioisotopes, tracers, which are injected into the subject [19]. The radiation is measured using a ring of detectors around the subject. The qualitative measurements are performed in the reconstructed images. The used tracer is designed for a specific purpose, so that the biochemical processes within the living organism can be studied. The objectives of PET imaging are several, and concerns metabolism, physiology, function, and morphology. It is for example possible to measure blood flow, identify functional areas in the brain, and study the metabolism in tumours.

A dynamic imaging sequence in PET starts with the injection of the tracer substance into the blood of the subjects. The data collection is done over different pre-programmed time intervals after the injection. The reconstructed image data consists of a frame (volume image) for each time interval, and the volume is divided into slices. It is a 4D data set. However, if each slice is viewed as a scene, the data set consists of as many multitemporal images as there are slices.

A characteristic feature of PET images is the large additive noise. The noise is often of the same magnitude as the signal.

3.2 Gamma camera imaging

The gamma camera is used for the same purposes as PET, and the study is performed in a similar way. In this case the tracers emit photons which are detected. The images are not divided into slices, but are a projection of the activity in the imaged volume. Single photon emission computed tomography (SPECT) is based on a rotating gamma camera.

Two characteristic features of gamma camera images are that they are projections, and that the noise is signal dependent and Poisson distributed noise is present.

3.3 Magnetic resonance tomography, MRT

MRT is based on the phenomenon called nuclear magnetic resonance [6]. It appears in nuclei which have an intrinsic angular momentum, called spin. The nuclei can be excited by supplying electromagnetic energy, and the nuclei then enter a higher state of energy. It is not stable in this state, so when the energy is turned off, the nuclei return to the static level, emitting the absorbed energy. It is this signal which is detected.

When performing an MRI scan, the subject is placed in a strong magnetic field, usually supplied by a supraconducting magnet. The acquired data from slices, or volumes, is defined by using gradients in the magnetic field. The common model describing the MR image parameters in the reconstructed image involves two spin relaxation components T_1 and T_2, and the concentration ρ of the imaged nuclei. Usually hydrogen is used. The image appears to be an anatomical map.

Two characteristics of MR images are that the additive normally distributed noise is in principle uncorrelated between pixels, and low (a few percent of the signal).

3.4 Landsat thematic mapper (TM), satellite imaging

Satellite imaging uses CCD arrays or other sensors for collecting data from several wavelength bands. The satellite Landsat TM collects seven wavelength bands for each scene.

Two characteristics of Landsat TM images are that the additive noise is in principle uncorrelated between pixels, and low (a few percent of the signal).

4 Developed methodology

The main contributions of the work described in this thesis are presented in this section.

4.1 Extending the strategy for multivariate image analysis

The work presented in [7] outlines a strategy for supervised classification of multivariate images through interactive explorative work using both scene space and feature space. It is based on PCA, and uses painting of the PC images and score plots combined with the user's knowledge of the application problem to obtain a classified image.

When using MIA for analysis of very noisy multivariate image data, such as PET image data, the PC images will not show the dimensionality reduction which is expected for very correlated data sets. Structure is present in higher dimensions. MIA can not clearly demonstrate the reason for this. By introducing new visualization tools and image modeling, studies of the variance directions captured by the eigenvectors for high-dimensional noisy data sets become feasible.

The analysis of a multivariate image can result in proposals for preprocessing of the image. Preprocessing can be very useful for different tasks and can be incorporated into MIA.

It is possible to use a ROI when performing PCA. This is referred to as a local PCA. The effect of a local PCA is that only the outlined pixel vectors are included in the analysis. The usage of this option has been explored and incorporated into MIA.

The conclusion from these extensions to MIA is that MIA could be used in an iterative way. The user can then explore the usage of a local PCA, and also the effects of image characteristics like noise on the PC images. Suggestions for preprocessing can be tested. Synthetic images are a useful, and sometimes the only, way to perform the analysis. When a satisfactory and understandable result is achieved, the developed strategy of preprocessing and analysis is applied on the real image data set.

4.1.1 Image modeling

Real image data can be very complex. One way to explore the characteristics of real image data is to create a synthetic image with the interesting properties. The synthetic image can then be used to analyse the specific characteristics of images from different applications under controlled conditions. Image modeling is proposed to be a part of the MIA strategy. By using modeling it is possible to reduce the dimensionality, and to create a clear-cut situation for the key characteristics of the real imagery.

I have used synthetic multivariate images extensively for creating visualizations of how additive and signal dependent noise is handled by the PCA. I have also used synthetic images for visualization of a PCA of noise-free image data, and for visualization of the influence of the spatial signals on the eigenvectors.

4.1.2 More visualization tools

If modeling of the images is used, a more favourable situation is created for visualization of the image, the PC transformation, and the result. MIA does have visualization tools for this, but improvements are needed in order to exploit the full potential of image modeling. Further, there is a need for aid in the interpretation of the PC images. A visualization tool specifically aimed to meet this need has been developed.

The eigenvector-scatter plot

This visualization shows the direction and magnitude of an eigenvector projected onto a subspace (a scatter plot) in feature space. By displaying the original image bands, the eigenvector-scatter plot, and the PC images simultaneously, it is possible to understand the connections between the data, the transformation, and the result.

The eigenvector-eigenvector plots

Iterative PCA generates a number of transformations and it can be hard to judge from the PC images if they differ or not. One way to do a crude comparison of the transformations is to measure the angle between eigenvectors in the two sets.

I have developed two visualizations tools for comparison of transformations. Both calculate the angle between two normalized vectors in a high-dimensional space as $arccos(\mathrm{e}_i \cdot \mathrm{e}_j)$. One is called the eigenvector-eigenvector (one-by-one) plot. It measures and plots the angle between corresponding eigenvectors in the two compared sets, i. e. the angle between the two first eigenvectors, etc. The other is called the eigenvector-eigenvector (one-to-all) plot. It measures and plots the angle between one eigenvector in one set and all eigenvector in the other set.

Using multiple views of the data

An other way to explore the difference between PC transformations is to use multiple views of the data and then to paint and transform pixel vectors between the different views. I have used three different views of the data simultaneously, in order to compare different PC transformations. One view is the scene space, which is the same for all variables. An other view is using the variable axes in the original feature space coordinate system to create scatter plots of the bands. A third view is using the rotated (and possibly scaled) coordinate axes in the coordinate systems obtained after a PCA for creating score plots (scatter plots of PC images). The third view of the data includes scaling operations of the feature space, because for example preprocessing by scaling the bands differently means scaling also of the corresponding coordinate axes.

When exploring several different views of the data, the pixel vectors can be painted in scene space or in feature space, and then transformed to an other view. If the pixel vectors are outlined in scene space, they can be transformed to any view of the feature space. If they are outlined in feature space, it is possible to first transform the pixel vectors to the scene space and then transform them to the desired feature space view.

The ROI-eigenvector plot

It is often desirable to interpret the PC images in a way that is meaningful for the application. The interpretation is preferably formulated from the signals in scene space, because this is the space which normally is used in the applications. I have therefore created a visualization tool in which the mean values in the ROIs outlining the interesting signals in scene space are plotted together with the elements of an eigenvector. The plot reveals whether an eigenvector is correlated to the spatial signals in scene space. This makes it possible to formulate an explanation for the appearance of a PC image in terms of the imaged signals.

4.1.3 Incorporating preprocessing in MIA

The analysis can result in proposals for preprocessing of the analysed image. Preprocessing is here used in a very wide sense. It could mean to outline a ROI and then

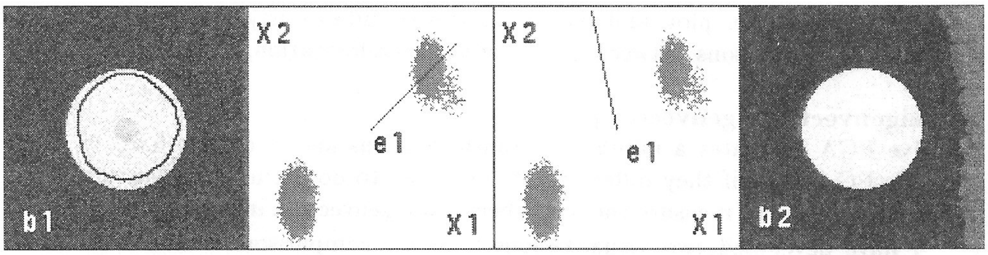

Figure 3: A synthetic multivariate image with two bands $\mathbf{b}_1$ and $\mathbf{b}_2$ consisting of three spatial signals. The left eigenvector-scatter plot shows the first eigenvector $\mathbf{e}_1$ obtained through a PCA. The right eigenvector-scatter plot shows $\mathbf{e}_1$ when the indicated mask is used. The indicated mask selects the upper right clusters in the feature space representation.

perform a local PCA, it could also mean to process the data in some way and then perform a PCA. Of course combinations are possible.

Performing a local PCA

The usage of a ROI restricts the spatial area under investigation. The ROIs can be outlined interactively in the image, outlined interactively in a scatter plot and transformed to the scene space, or created in some other way. The ROI specifies which pixel vectors should be used in the calculation of the eigenvectors. The effect is most clearly demonstrated using examples.

A synthetic image with two bands and three spatial signals is shown in Figure 3. After a PCA of the image, the first eigenvector indicated in the left one of the two eigenvector-scatter plots is obtained. The eigenvector obviously points out a maximum variance direction between the two large clusters in feature space, corresponding to the background and the large spatial signal in scene space. If the indicated ROI is used, a local PC transformation is obtained. Then the background cluster will not influence the eigenvectors, and a maximum variance direction for the remaining two clusters is pointed out, as seen in the rightmost eigenvector-scatter plot in the figure.

The result for scene space is demonstrated using a multivariate MR image consisting of four T_1 weighted and four T_2 weighted images of the same slice for a healthy person. From a PCA of this image eight PC images are obtained, the four first are shown in the upper row of Figure 4, PC1 to the left, PC4 to the right. Outlining a ROI covering only the brain and then applying a local PCA results in the first four PC images shown in the lower row. Comparing the two image sets visually, it is seen that using a ROI covering the brain makes the PCA extract the structures of the brain into fewer PC images. A possible explanation for this is seen in Figure 3. If the whole image is used, the first eigenvector will point out a direction from the background cluster to the object clusters. The next direction must be orthogonal, so the first choice restricts the following choices. If a ROI is used, the first eigenvector points out a maximum variance direction for the object clusters, and PCA continues to choose directions only for the object clusters.

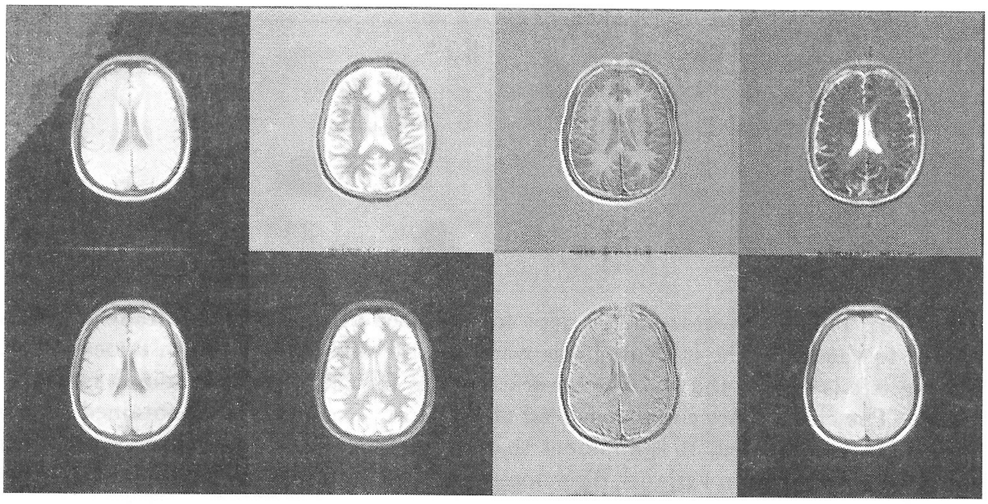

Figure 4: The upper row shows from left to right; PC1 to PC4 after PCA of a multivariate MR image consisting of four T_1 weighted and four T_2 weighted images of the same slice. The lower row shows the result if a ROI is used. The structures are concentrated into fewer PC images.

Preprocessing of the image bands due to noise

The considered noise characteristics were additive and signal dependent noise. Additive noise can be normalized for each band. Signal dependent noise can be stabilized using variance stabilizing transformations of the data. For example, I used a square root transformation to stabilize the Poisson distributed noise [5] in gamma camera images.

An example with a synthetic image shows the effect in feature space of using noise normalization. In Figure 5 the feature space spanned by the previously used synthetic image is shown to the left. The first eigenvector obtained from a local PCA is indicated. The direction pointed out by the eigenvector is influenced by the high noise in the X_2-direction (vertical), and does not consider the direction between the two clusters to be the maximum variance direction. This means that the two clusters are not optimally contrasted in PC1. Compare this to the case of using noise normalization and a local PCA, shown to the right. After noise normalization, the clusters are circular instead of elliptical. There is no noise direction which can be considered to be a maximum variance direction, instead the first eigenvector points out a direction given by the centres of gravity for the two clusters. The corresponding signals in scene space will appear with better contrast in PC1.

An example demonstrating the result in scene space is shown in Figure 6. The multivariate image consists of ten slices from a dynamic PET sequence using ^{11}C-L-deuterium-deprenyl as a tracer in a patient with temporal lobe epilepsia. The multivariate image is subject for a PCA (no ROI is used). The obtained PC images PC1 to PC4 are shown in the upper row, left to right. Structures are clearly visible only in PC1. It is possible to estimate the background noise in the bands using reconstruction data. A normalization of the noise in the image bands was done.

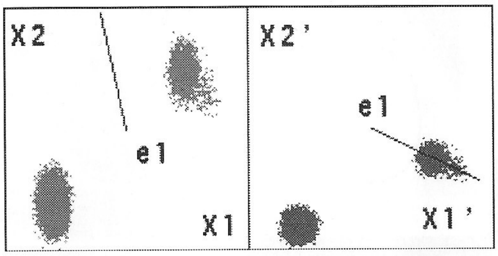

Figure 5: The eigenvector-scatter plot for the used synthetic multivariate image is shown to the left. The indicated eigenvector is the one obtained from a local PCA. To the left is shown the eigenvector-scatter plot for the noise normalized synthetic image. The clusters are circular instead of elliptical. The eigenvector obtained from a local PCA is indicated. It is apparent that the eigenvector considers the two clusters to span the maximum variance direction.

PCA was applied to this preprocessed data set, resulting in the PC images PC1 to PC4 shown in the lower row. Structures are now clearly visible in the first three PC images. A possible explanation for this result was derived using the synthetic image example. When using the original data, successive noise directions are chosen by the eigenvectors, see Figure 5. The signals will not be optimally handled.

The theory for the presented noise normalization is nicely presented by Green et al. [10]. In short, performing a normalization of the additive noise in the different bands will result in PC images sorted after signal-to-noise ratio (SNR). When I have applied MIA on the application examples, the results from investigations of the noise in different bands often motivated preprocessing.

It should be noted that using the correlation matrix also means that the variables are normalized, but then the *total* variance in a band is normalized. In all cases where I have used normalization, only the variance due to *noise* is normalized.

5 Summary of the papers A-G

The papers can be clearly divided into two categories. Papers A-C present the software, the developed methodology, and preliminary results. In papers D-G the methodology is applied to the applications, and the results are evaluated.

5.1 Paper A

MUSE is the software which was used in the work presented in this thesis. It is an experimental software for multivariate image analysis which is created by implementing several multivariate transformation and classification algorithms, and by supporting them with visualizations of the data, the performed transformations, and the results. The paper considers the design and implementation of MUSE, and preliminary results are demonstrated. The implementation was done on a specialized image processing workstation in order to achieve the needed interactive environment.

MUSE was also designed for exploratory work using multivariate statistical

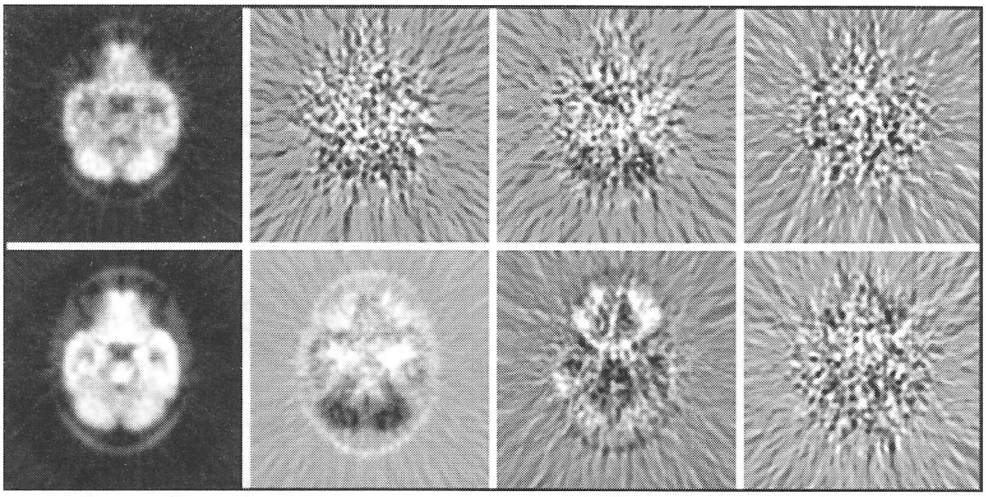

Figure 6: The upper row shows from left to right; PC1 to PC4 after PCA of a multitemporal PET image consisting of the same slice from ten frames. The lower row shows the result when noise normalization is used. The structures are concentrated into fewer PC images.

methods applied to univariate grey scale images made multivariate. A grey scale image can be made multivariate by adding new image bands obtained through filtering. The filters can add local information, such as texture, to the grey scale image. This aspect of MUSE is not part of the present thesis.

Our implementation of MUSE consists of the following components. For general visualization of the data set, histograms, scatter plots utilizing painting to/from scene space, and pseudo colour images are available. PCA is available. Linear regression is available. Three classifiers are available; discriminant analysis based on Bayes' decision theory, nearest neighbour classification, and box classification. It is possible to outline arbitrary ROIs in order to restrict the spatial area involved in the transformations, or to give training areas.

When I implemented the higher level parts of MUSE which concerns PCA, special attention was given to the visualization of the transformation and of the results together with the original data. This was done in order to increase the understanding of the obtained transformation and result. Both scene space and feature space were used. This paper contains a description of the software, so the usage is explained but not demonstrated. In paper C the visualizations are demonstrated using examples.

All visualizations and their parameters (except those involving alpha-numeric characters) were designed to be interactively activated. The input image bands represent themselves, but the PC images represent both themselves and the corresponding eigenvector, depending on the situation.

This work was mainly carried out 1988 to 1990, when the planning and the first implementation of the MUSE software was done. The first report on MUSE was [2]. However, the software was modified over time and a stable version was not ready until 1993.

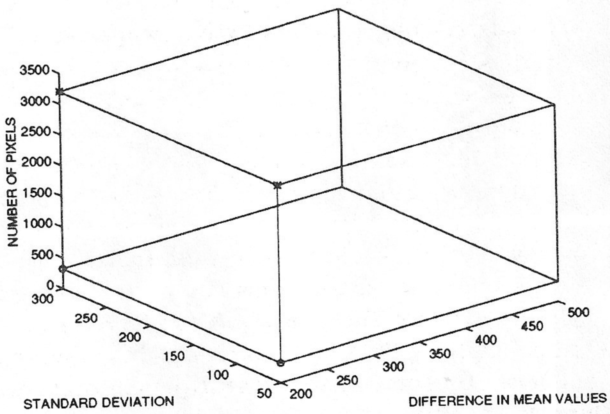

Figure 7: The used parameter space. The two upper marked corners define a synthetic image with two bands, and so does the two lower marked corners. Only one parameter differs between the two images. PCA were applied to the images, and the angular difference between the obtained first eigenvectors was studied.

5.2 Paper B

The first studies of synthetic and real PET images showed promising results [20] [17] and motivated a more general study. This paper investigates how varying the image parameters for a synthetic image influence the first eigenvector obtained using PCA. I have designed the multivariate model image to consist of two image bands. Only two normally distributed signals are present in the scene. The parameters mean value, standard deviation, and number of samples for the signals are investigated.

In order to get a restricted parameter space, the studied parameters was transformed to a new set of parameters:

- The number of samples in the scene is fixed. Two combinations of sample size for the two signals were chosen.
- The mean value was fixed for the signal consisting of the major part of the samples, and only two mean values were possible for the other signal. The difference between the mean values could then only be one of two values.
- The standard deviation was set to one of two possible values. Each band had the same standard deviation for both signals.

This way of limiting the parameter space means that when the parameters for one signal in one band is chosen, the parameters for the other signal in this band is fixed too. The created parameter space is shown in Figure 7.

Each corner of the rhomb in the figure defines an image band. Only one parameter was allowed to change for the bands when creating a two-band multivariate image, so the used multivariate images are defined by the edges in the rhomb. When comparing sets of eigenvectors obtained from different multivariate images, only one parameter is allowed to change for the images, so each comparison is done for two parallel edges in a side of the rhomb. There are six sides in the rhomb, and two parallel edges for each side, making a total of twelve comparisons.

The angle between the derived first eigenvectors was calculated for the twelve cases. The cases simulate situations in which the object changes size, there are differences in signal levels, and there are differences in noise levels during the acquisition. The conclusion from the study was that the parameter which could most easily be controlled was the standard deviation. Normalization of the standard deviation made the PCA less sensitive to changes in the other parameters. A possible explanation is that if the bands have different standard deviation (noise levels), the signals appear as hyper-ellipsoids in feature space. This structure of the signals, caused by the noise, has a preferred variance direction which can be recognized as a maximum variance direction when applying PCA. PCA is a data-driven technique and can not separate signal from noise. By normalization, the hyper-ellipsoids are transformed to hyper-spheres, which do not have any preferred variance direction.

The result from the numerical experiments was the proposal to preprocess the data by normalizing the noise in each band before applying PCA. This was tested on a PET sequence, and visual inspection supported by measurements of the SNR indicated that the method improved the obtained result when using PCA.

A small experiment was performed, in which the influence of cross-correlation between pixels was studied, but no obvious conclusions could be drawn from this.

As a final result, it was shown that the normalization of the noise could be done by scaling the covariance matrix. The obtained matrix represents the normalized data set.

I would like to mention that one of the reviewers of the paper indicated that there was theoretical work done on PCA and different noise in different bands. I found the work by Green et al. [10] in the remote sensing area. Their model is different, but the methods are equivalent.

This work was mainly carried out in 1992.

5.3 Paper C

The strategy of MIA [7] is in principle incorporated in MUSE. Several improvements of the strategy were developed and these are presented in this paper.

I suggest three major improvements. One is to use image models when exploring the possibilities for segmentation of the image. An other is to incorporate preprocessing in MIA. Combining these two proposals suggests that MIA should be performed in an iterative manner, where different preprocessing techniques can be tested in combination with PCA. MIA relies heavily on user interaction, so the set of visualization tools should be extended, and this is the third suggestion.

The suggestions were used to create an extended model of MIA, see Figure 8, in which a feedback loop after PCA, and different possibilities for preprocessing, are present. The feedback loop is generated from user interaction, in which different visualizations of the performed PC transformation are presented. For this purpose the eigenvector-scatter plot and the eigenvector-eigenvector plots were introduced and their usefulness demonstrated (see previous section for a demonstration of the eigenvector-scatter plot).

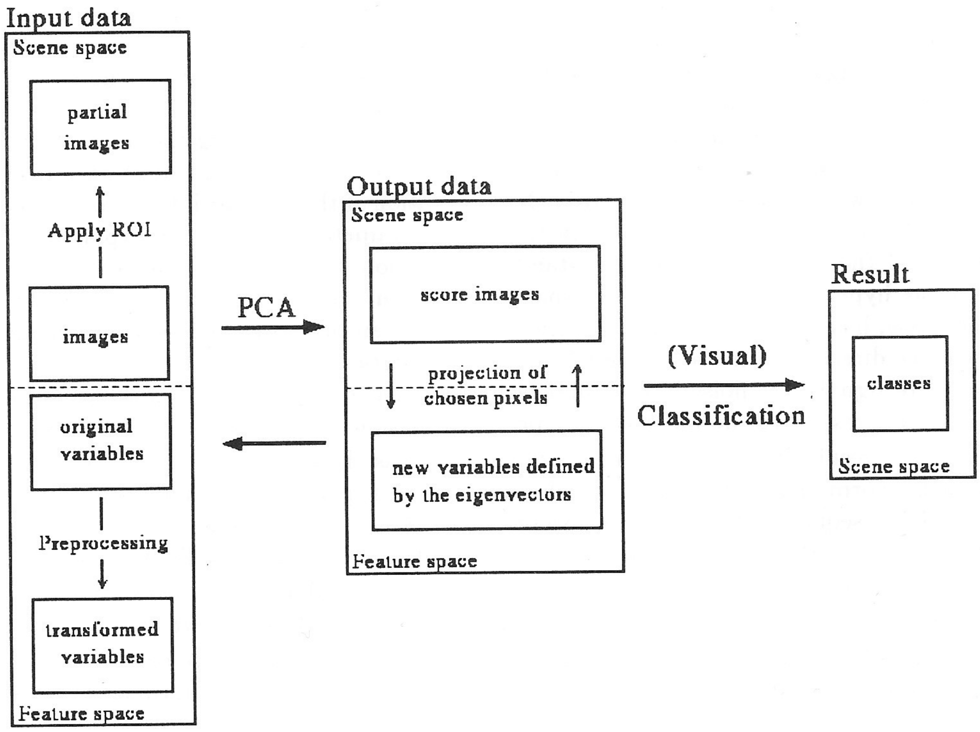

Figure 8: The model of extended MIA. Preprocessing and a feedback loop are made possible by using image models and new visualization tools.

A new visualization tool used for the interpretation of the PC images, the ROI-eigenvector plot, was introduced and demonstrated. It shows the correlation between the spatial signals and an eigenvector, and this gives an indication of the spatial signals importance and weighting in the corresponding PC image. It was demonstrated using a PET body scan example. The second PC image contrasted different organs in the image. Two spatial signals representing the early dynamic phase (the pancreas) and the later static phase (the renal pelvis), respectively, was outlined. The ROI-eigenvector plot for the two spatial signals and the second eigenvector is shown in Figure 9. From the figure it is clear that the eigenvector is positively correlated with the early signal from the pancreas. It then changes to negative correlation with the late signal from the renal pelvis. The second eigenvector was interpreted as describing a contrast between early dynamic and the later, more static, signals. This interpretation is also valid for the corresponding PC image.

This work was performed in 1992 and 1993.

5.4 Paper D

This work demonstrates the possibility to handle applications with different noise characteristics consistently with MIA. Gamma camera image data has signal dependent, Poisson distributed, noise. MIA was used to point out the problem with applying PCA on such data sets using synthetic gamma camera image data. It was shown that

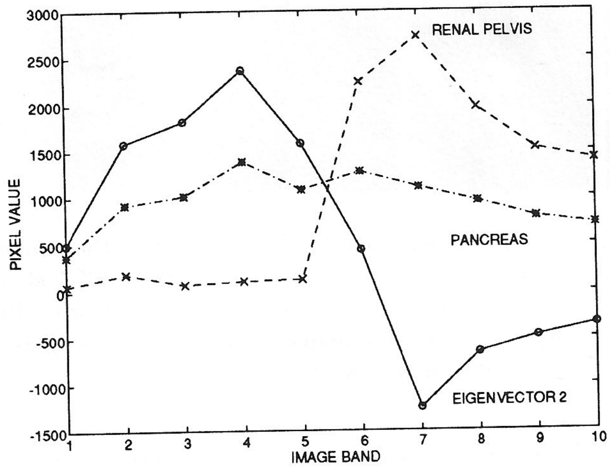

Figure 9: The ROI-eigenvector plot for two relevant spatial signals and the second eigenvector. The eigenvector correlates with the pancreas in the early phase, and with the renal pelvis in the later phase.

the obtained eigenvectors could point out noise directions in feature space. A square-root transformation of the data was used as preprocessing. The noise is stabilized and becomes whiter [5].

After the proper preprocessing was established, PCA was applied to the gamma camera data. It was demonstrated that the stabilization of the signal dependent noise using the square-root transformation improves the behaviour of the SNR in the PC images. One PC image enhanced structure which was very hard to see in the non-stabilized PC images.

The PET image data was processed in analogy with the gamma camera image. PET image data has large additive noise. The noise was normalized, and after this preprocessing, the PC images were sorted after decreasing SNR. The noise will after preprocessing become in principle white.

It was pointed out that the proposed preprocessing in both cases could be done automatically.

Initial studies of PET was performed in 1991 and in 1992. The gamma camera study was done in 1993.

5.5 Paper E

An important issue in clinical work is that outlining a ROI covering clinically interesting information is subjective in nature. Two doctors can not be expected to outline the same ROI. This paper addresses the use of PCA of PET image data from a clinical point of view.

A complex ten-dimensional synthetic image containing three signals simulating different kinetic patterns which are not corrupted by noise was subject for a PCA. The resulting PC images span only three dimensions. This pointed out the dimensionality reducing properties of PCA. When inspecting the three eigenvectors, an interpretation

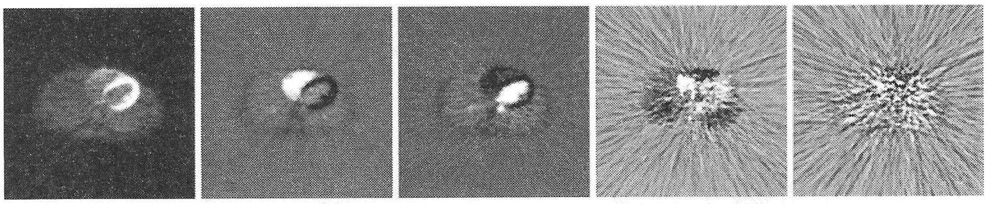

Figure 10: The first five PC images obtained for a study of the oxidative metabolism in the hart using ^{11}C-acetate. Left to right: PC1 to PC5. PC1 shows the weighted average, dominated by the very high uptake in the hart muscle. PC2 clearly show the right ventricle, and PC3 the left ventricle. The ventricles display different kinetic patterns, and this is captured in the two PC images.

of corresponding PC images was possible. The first PC image could be interpreted as a weighted mean value image, and the two following PC images contrasted the three signals to each other in two different ways. This suggested that clinically interesting structures can be visualized in a better way using PCA, and that it could aid in the identification of structures with different kinetic pattern.

MIA was used to demonstrate how preprocessing of a synthetic image with additive noise improves the PC images obtained through a PCA.

PCA was then applied to five different PET data sets utilizing four different tracers. The PCA was performed fully automatically. No ROI was used, and the preprocessing was done using reconstruction data available together with the image data. All used data sets displayed the same behaviour. The first PC image was a weighted mean value image. The next one or two PC images, depending on the number and complexity of the signals, showed the different kinetic patterns contrasted. Structures were visible in a few higher PC images, but could not be interpreted. See Figure 10 for an example.

The features of the proposed methodology relevant for clinical work was pointed out. The dimensionality reduction reduces the number of relevant images. Further, the whole data set is used in the analysis. A very important aspect concerns the absence of a kinetic model in the analysis. This excludes model based restrictions.

Much of the initial experiments were done in 1991 and in 1992. The clinical study was done in 1994.

5.6 Paper F

The paper presents an initial study of PCA applied to functional MRI (fMRI) data. fMRI is used to image changes in the blood oxygenation level dependent (BOLD) signal in the brain. During the acquisition of the images, the subject changes from a rest state to an active state using a predefined (motor or sensory) activation and timing. One task for an analysis of the acquired image data is to identify the activated regions in the brain of the subject.

MR image data is not noisy to the extent of PET or gamma camera data, so preprocessing due to noise was not performed. In the case of fMRI, the images display three characteristic features. Large parts of the image do not contain any signal, large blood vessels show very high signal, and the sought for stimulated areas show a weak

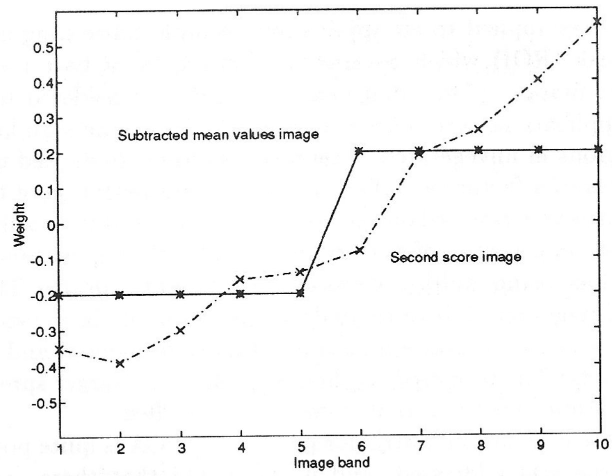

Figure 11: The two linear combinations used to create functional maps. The second eigenvector is smoother and displays a time delay.

signal. A ROI was used to define the brain of the subject, but the ROI excluded the large blood vessels.

A local PCA was performed. It resulted in a second PC image where the investigated subjects had $0 - 30\%$ better SNR than a conventional subtraction of mean value images from the rest state and the activation state. The second PC image could thus be used as a functional map.

The obtained second eigenvector reflects the timing of the experiment, without any a priori knowledge of the time course of the activation. Using the second eigenvector as a correlation function showed interesting results. Higher correlation coefficients, than what was obtained using the time course of the experiments, were acquired for areas in the image. This suggests that the second eigenvector could be used to create correlation maps. The second eigenvector displayed a time delay compared to the actual activation, see Figure 11, which is reasonable.

This work was performed during 1993.

5.7 Paper G

In the area of remote sensing, PCA is a quite commonly used method for analysing multitemporal and multispectral data sets. This paper was aimed at reviewing the used techniques and to show how MIA can be used for a remote sensing application.

Several different approaches for using PCA is reviewed in this paper. The conclusion was that in many approaches the data set is preprocessed in one way or the other, for example by excluding bands or by performing a local PCA. The chosen preprocessing is used, and results are obtained, but it was noted that usually no general conclusions about the obtained PC images are presented.

MIA was used to explore how background pixels and background noise affects the eigenvectors, and the PC images.

Then MIA was applied to an application example concerning surface soil classification. A mask (ROI) which covered only unvegetated bare soils was created. Landsat thematic mapper (TM) image data can not be considered to be very noisy. Still, for some applications, the noise can be a problem. The standard deviation in homogeneous regions in unvegetated areas was measured. It showed upon differences between the bands of a factor two. This motivated normalization of the noise.

A local PCA was performed on the normalized data and the result was compared with two other standard ways of performing PCA, with and without a mask. The comparison was done using multiple views of the data and painting. The score plot for the first two PC images for all investigated images was used. In the score plot created from a PCA of the noise normalized data, clusters were painted and transformed to the other score plots. The proposed methodology showed a larger spread between the clusters, an indication that the signals were better handled.

The use of the correlation matrix for performing PCA is quite popular in remote sensing. This issue was addressed, and it was noted that there are no statistical reasons for its use in normal cases. Some applications have displayed more favorable PC images using the correlation matrix, but with little explanations of the reason for this. MIA could be a way to generate interpretable and reproducible results.

This work was mainly carried out in 1993. It is developments of preliminary results presented in [18].

6 Closing remarks

6.1 Conclusions

This thesis presents a methodology for interactive explorative analysis of multivariate images utilizing principal component analysis. The work consists of several parts. The first part was the design and implementation of the MUSE software. Then, an existing methodology was used and extended. The proposed extensions consisted of the introduction of a feedback loop after PCA, and the incorporation of preprocessing and image modeling. These methodological extensions were made possible by extending the software with new visualization tools. Finally, the developed methodology was applied to images from several disciplines with different image characteristics.
In the thesis the following useful partial results are presented:

- It is possible to use MIA to develop preprocessing routines for images with different noise characteristics. This was used to include a new class of images for analysis; images with very large noise.
- PCA of PET images was shown to have a potential to be incorporated in ROI analysis.
- The developed strategy for creating PC images with high SNR and enhanced features can easily be separated and brought to the end user.

In conclusion, the results strongly indicate that the developed methodology has a potential for reducing the dimensionality of the analysed imagery, enhancing the structures present, and incorporating the user in interactive explorative work. The methodology can be used for preprocessing of the analysed imagery before a classification or a visual or automated segmentation step.

6.2 Future work

The work described in this thesis can be broadened in many directions.

- The work presented in this thesis has concentrated on preprocessing of the analysed imagery. A natural continuation would be to carry out classification and segmentation. Especially the PC images obtained from PCA of PET images should be suitable for this.

- It would be possible to replace PCA with some other, not so rigid, technique. The relatively simple modeling of the image data presented would then have to be more elaborate.

- The acquired knowledge about using PCA for preprocessing and visualization is suitable for investigations concerning multi-tracer PET data. If registration is performed on such PET image data sets, the presented methodology would be applicable. I believe that further developments would be needed, particularly in image modeling.

- Functional MRI is in rapid development, and extended MIA could be included in the analysis of the data, especially as the data sets tend to be high-dimensional. The possibility to perform interactive exploratory work for creating functional maps with high SNR, and the possibility to use the eigenvectors as correlation function could be one way to explore the data sets.

- MIA already exists as a software in the remote sensing area. I therefore believe that MIA, with the proposed extensions, is particularly suitable for work in this application area.

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