Manuscript of:
Piotr M. Szczypinski, Michal Strzelecki, Andrzej Materka, Artur Klepaczko,
MaZda – A software package for image texture analysis,

Published:
Elsevier, Computer Methods and Programs in Biomedicine,
Volume 94, Issue 1, April 2009, Pages 66-76, ISSN 0169-2607,
DOI: 10.1016/j.cmpb.2008.08.005.

MAZDA – A SOFTWARE PACKAGE FOR IMAGE TEXTURE ANALYSIS

Piotr M. Szczypiński, Michał Strzelecki, Andrzej Materka, Artur Klepaczko

Institute of Electronics, Technical University of Łódź
Wólczańska 211/215, 90-924 Łódź, Poland
piotr.szczypinski@p.lodz.pl

Abstract –MaZda, a software package for 2D and 3D image texture analysis is presented. It provides a complete path for quantitative analysis of image textures, including computation of texture features, procedures for feature selection and extraction, algorithms for data classification, various data visualization and image segmentation tools. Initially, MaZda was aimed at analysis of magnetic resonance image textures. However, it revealed its effectiveness in analysis of other types of textured images, including X-ray and camera images. The software was utilized by numerous researchers in diverse applications. It was proven to be an efficient and reliable tool for quantitative image analysis, even in more accurate and objective medical diagnosis. MaZda was also successfully used in food industry to assess food product quality. MaZda can be downloaded for public use from the Institute of Electronics, Technical University of Lodz webpage.

Keywords – texture analysis, feature reduction, data classification, image segmentation

1. Introduction

A texture perceived by humans is a visualization of complex patterns composed of spatially organized, repeated subpatterns, which have a characteristic, somewhat uniform appearance [1]. The local subpatterns within an image are perceived to demonstrate specific brightness, color size, roughness, directivity, randomness, smoothness, granulation, etc. A texture may carry substantial information about the structure of physical objects. In medical images it describes internal structure of human tissues or organs. Consequently, textural image analysis is an important issue in image processing and understanding.

Although textures are easily perceived by humans, there is no strict definition what constitutes a texture in image processing terms. Humans usually assess texture only qualitatively, while often quantitative texture analysis is required, e.g. in systems for medical diagnosis. To perform such quantification, mathematically defined texture properties have to be generated by means of texture analysis computer programs. These programs are usually based on general purpose software like Matlab [2]. They are capable of solving particular problems for particular categories of images with specifically chosen textural properties. If the problem or image category differs, such software tools become insufficient. Therefore, a choice of other texture descriptors or image analysis methods is necessary, which is a non-trivial problem. Mazda offers a new approach and seems to be a more appropriate tool to perform the task. The software was already utilized in many areas including MRI measurement protocol optimization [3], various medical studies [4-16], food quality studies [3, 17-19], etc.

In 1998, the European COST B11 (1998-2002) project was started and one of the objectives was the development of methods for quantitative textural analysis of magnetic resonance images. At that time there was no commercially available software capable to conduct a quantitative analysis of texture within freely selected regions of interest (ROI) and to provide an interpretation of computed results. MaZda was the first program created to satisfy these objectives. In fact, its development started two years earlier in 1996. It was a program for texture analysis in mammogram images [20]. The first version of MaZda computed textural features derived from a co-occurrence matrix, which in Polish is named *Macierz Zdarzeń*. The name of the software is an abbreviation of this term. In 1998, several procedures developed and implemented in NMRWin [21] program at the German Cancer Research Center were adapted and implemented in MaZda. Later, in 1999, procedures for statistical and discriminative analysis of feature vectors were developed. For the last ten years MaZda has been continuously improved. Within framework of COST B21 project (2003-2007), MaZda was extended by adding color and 3D image analysis, 2D and 3D image segmentation, data classification, analysis automation and other functions.

The program code has been written in C++ and Delphi™ with the use of OpenGL libraries. It has been compiled for computers that use Microsoft Windows® 9x/NT/2000/XP operating systems. The package includes two executable files named MaZda (image processing and computation of textural features) and b11 (for data visualization, classification and segmentation). It has been widely used by participants of COST B11 and B21 projects, followed by other collaborating scientists and students in numerous research areas.

MaZda is accompanied by an open source C++ library (MaZda SDK). It includes classes for accessing and storage of images, regions of interest and report files. Thus, by means of the available library, MaZda users are able to create their own image analysis modules. MaZda can execute such modules and can exchange data with them. Moreover, it has a built-in script interpreter engine. As a result, users can define sequences of computations to be executed on collections of images.

There are only few other examples of image texture analysis software available. The other non-commercial packages like KeyRes [22] and LS2W [23] provide only a limited number of Mazda functionalities.

KeyRes Co-Occurrence Features is a software which allows estimation of co-occurrence based texture features for monochrome and color images (after converting into grayscale). It supports several basic image formats like TIFF, GIF, JPEG and BMP. Texture features are estimated in windows with variable size, for different inter pixel distances for evaluation of CO matrix. 3D image visualization, correlation map between estimated features and plot, and the features histogram are also available. KeyRes was written using C/C++ language and may be run under Matlab environment.

The LS2W software is a part of WaveThresh3 package for performing statistics based on wavelet techniques. The package is an add-on to the popular statistical S-Plus software (Insightful Corporation). It includes both various wavelet transforms and a number of statistical techniques (also based on wavelet transform). Its applications involve image analysis. The LS2W applies the Non-Decimated Wavelet Transform [24]. This transform is suitable for a model of locally stationary wavelet processes. In contrast to the traditional, frequency-based Cramér representation, this model permits a location-scale decomposition of the covariance structure of time series which appear to be stationary within localized regions, though their form may evolve from one region to another. Transform coefficients estimated by this software are useful for characterization of textures which possesses locally stationary, multiscale structure.

2. Image analysis pathways in MaZda

There are several pathways of image analysis that are handled by MaZda package (Fig. 1). Starting with the input data, there is a choice between the analysis of 2D grayscale, 2D color or 3D grayscale images. MaZda implements procedures for loading of most popular standards in MRI. Also it loads Windows Bitmaps, selected Dicom formats or unformatted grey-scale image files with pixels intensity encoded with 8 or 16 bits. A user is given a choice between analyzing the image as a whole or analyzing freely defined regions of interest. (The region has to be shaped by means of MaZda's 2D or 3D region editors.) Depending on the choice made, the results of the image texture analysis are feature distributions within the image (feature maps), or text lists of features computed within regions of interest (feature vectors). Feature maps may be useful for image segmentation, while the feature vectors for classification of image content.

Feature vectors computed by MaZda include up to several hundred elements per individual region of interest. Such a large number of features, creating several-hundred-dimensional spaces, are not easy to handle by statistical analysis or by classifiers. Thus, MaZda employs techniques for reduction of feature vector dimensionality by selecting the most discriminative features for further analysis. There are several methods for feature selection, using various selection criteria, which can be chosen by the user.

There are three main pathways of analysis offered by the b11 module. The data (feature vectors) can be statistically analyzed and visualized to compute and display relations between features and classes of textures. In addition, there are methods implemented for supervised and unsupervised classification. The b11 may be used for formulating rules for texture classification or designing an artificial neural network classifier. Finally, feature maps can be employed for image segmentation.

3. Regions of interest

Regions of interest are sets of pixels in 2D images or voxels in 3D images selected to be analyzed. Defining a specific region of interest (ROI) concentrates the computation effort on an image fragment that is relevant to the goal of analysis and thus helps to avoid unnecessary processing. ROIs are of great interest in biomedical image processing applications. For example, tomography images of the human body contain various kinds of organs or tissues. To analyze image properties in a selected organ and not in the surrounding tissue, the image fragment corresponding to the organ must be defined, as the ROI for the analysis.

The ROIs in MaZda can be of arbitrary shape. The software allows definition of up to 16 ROIs within a single image. These regions can overlap if required. If there are more then 16 regions required for the analysis, they have to be analyzed successively, up to 16 at a time.

ROIs can be loaded from a file or defined with MaZda ROI editors. To edit 2D ROIs (Fig. 2 a), drawing tools for lines (with various line thickness), squares, rectangles, circles, ellipses are used. Also, tools based on image grey level thresholding and flood-filling are available. Additionally, to process a region shape, tools based on morphological transformations such as regions erosion (removes a layer of pixels), dilation (adds a layer of pixels), closing (smoothes boundaries, fills-in small holes) or opening (smoothes boundaries, removes small groups of pixels) can be used.

Volumetric ROIs within 3D (Fig. 2 b) images, e.g. images from magnetic resonance or computer tomography scanners, can be defined with an appropriate set of tools. The simplest way is to assemble ROI from predefined blocks, such as spheres, tubes, cubes and tetrahedrons. Blocks can be placed within 3D image space at chosen locations. The orientation, size and proportions of blocks can be adjusted freely. Other ways to create 3D ROI are to perform image segmentation with the image grey-level thresholding and flood-filling, or to edit region cross-sections with the 2D ROI editing tools. The most advanced tool for 3D region editing implemented in MaZda is the deformable surface [25, 26]. It is a mathematical model of an enclosed surface that starts from an ellipsoidal shape and deforms upon local image characteristics. The deformation process aims at fitting the surface at locations of high image gradient or locations having a gray-level close to the selected threshold value. The final shape of the model strongly depends on the initial shape and location of the surface, image contrast and some other parameters. Therefore, a deformable surface is implemented as an interactive tool allowing the user to adjust these parameters, to obtain the most satisfying shape.

4. Textural features

There are three major issues in texture analysis that MaZda assists with. These are: texture feature computation, texture segmentation and texture classification. Texture features are image characteristics able to numerically describe the image texture properties. Texture segmentation is the task of partitioning a textured image into regions, each corresponding to a perceptually homogeneous texture. Texture classification determines to which of a finite number of physically defined classes a homogeneous texture region belongs. Feature computation is usually the first stage of the image texture analysis. The results obtained from this stage are used for texture discrimination, classification or segmentation.

There are three categories of feature computation approaches that MaZda utilizes: statistical, model-based and image transform [26]. Statistical approaches represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. The model based texture analysis [1], using fractal or stochastic models, attempts to interpret an image texture by the use of generative image models and stochastic models respectively. Transform methods of texture analysis, such as Fourier, Gabor or wavelet transforms [27-29] represent an image in a space with a co-ordinate system which is related to the characteristics of a texture.

The user of MaZda package may select by means of the Options window controls groups of features to generate. The choices are: histogram, gradient, co-ocurrence matrix, run-length matrix, autoregressive model [30] and Haar wavelet [31] groups.

The most common statistical method for image feature computation is based on image first-order histogram. The histogram is computed from the intensity of pixels, without taking into consideration any spatial relations between the pixels within the image. Features are simply statistical parameters of the histogram distribution such as: mean brightness, variance, skewness, kurtosis and percentiles. Another statistical method derives features from the gradient magnitude map of the image. Based on the histogram of the image gradient a similar feature set is calculated for the image intensity distribution.

The gray-level co-occurrence matrix (COM or GLCM) is a second-order histogram, computed from intensities of pairs of pixels, where the spatial relationship of the two pixels in a pair is defined. The COM based features are derived from the matrix to demonstrate statistics, such as angular second moment, contrast, correlation, sum of squares, and various averages, variances, inverse moments and entropies [32].

The run-length matrix (RLM) holds counts of pixel runs with the specified gray-scale level and length. In MaZda, there are four various run-length matrices computed, for four directions of pixel runs: horizontal, vertical, at 45° and at 135°. There are five run-length matrix based features computed for each of the matrices: short run emphasis inverse moment, long run emphasis moment, grey level nonuniformity, run length nonuniformity and fraction of image in runs [32].

There are also model-based textural features computed by the software, which are based on a first order autoregressive model of the image [30]. The model assumes that pixel intensity, in reference to the mean value of image intensity, may be predicted as a weighted sum of four neighboring pixel intensities. These neighboring pixels are left, top, top-left and top-right adjacent. Therefore, the model has four parameters, which are weights associated to these pixels, plus a fifth parameter which is the variance of the minimized prediction error [3, 30].

The transform method of texture analysis implemented in MaZda is based on discrete Haar wavelet. The wavelet images are scaled up to five times, both in horizontal and vertical direction. It results in image transformation into twenty frequency channels. Energies computed within the channels provide data on texture frequency components and are used as texture characterizing features.

To check whether the features characterize an image texture exclusively and do not depend on any global image characteristics, such as the overall brightness or contrast, varied illumination or some other bias, a normalization procedure has been implemented. Normalization reduces dependency of higher order parameters on first order grey-level distribution. There are two image histogram normalization options available. One of them remaps an image histogram in a range with the mean luminance in the middle and a span of 3 standard deviations onto the white-to-black gray-scale range. The other remaps an image histogram in the range between the first and ninety-ninth percentile onto the white-to-black range [33]. The image normalization step is performed prior to the computation of textural features.

The other image transformation that precedes feature computation involves altering the number of bits used to encode the image intensity. The number of bits can be set up between 4 and 12. This can substantially change number of pixels in runs and the size of the co-occurrence matrix for certain images, which in result affects the processing times and results of computation based on RLM and COM matrices. Careful adjustment of the number of bits can help reduce the effect of random noise influence on texture features.

Summarizing, Mazda software allows computation of 9 histogram-based textural features, 11 co-occurrence-matrix-based features derived from 20 co-occurrence matrices produced for 4 directions and 5 inter pixel distances, 5 run-length-matrix-based features at 4 different directions each, 5 gradient-map-based features, 5 based on autoregressive model and up to 20 based on Haar wavelet transform. Altogether 279 descriptors that can characterize a grey-scale image texture. All the features can be computed within any ROI of the original image or the image after normalization, and with a different number of bits per pixel.

Methods for textural features computation implemented in MaZda require a gray-scale image as an input. On the other hand, it is evident that for camera images color often carries essential information required for image differentiation or recognition. MaZda may be used to analyze a selected color component (or channel) of the image, not only the image brightness. Therefore, there are several options for color to gray-scale transformation available, including conversions to Y, R, G, B, U, V, color saturation or hue channels. It is possible to combine features computed within different channels of the same image to obtain a comprehensive characterization of a color texture.

The computed feature vectors are presented in the report window (Fig. 3) in a form of a spreadsheet (the lower panel of the window). Each column of the table, except the first one, represents a region of interest for which the features were computed. The rows correspond to the particular features. Each column can be assigned a name, which in the later analysis will represent the class that the feature vector (or sample) belongs to. The upper panel of the window lists the input image and regions of interest filenames, as well as parameters for which the features were computed. The results of each individual analysis instance are presented in a separate tab page of the report window.

5. Geometric parameters

Two-dimensional regions of interest, which were primarily planned as masks for textural analysis, can be also viewed as images themselves. They represent silhouettes of two-dimensional objects that they cover and may carry key information for classification of such objects. Therefore, another approach for feature computation is to measure characteristics of these regions, such as location, orientation, size, geometry and topology descriptors, etc. The software computes parameters such as areas, perimeters, various diameters and radix, including Feret's and Martin's [34], as well as parameters of the inscribed circle, circumscribed circle, ellipsis and rectangle. Moreover, it computes various ratios of these parameters, like elongation, roundness and compactness. Most of such ratios are size invariant. Other size invariant parameters implemented in the software are first and second-order central moments [34]. The list of geometric parameters computed by MaZda may be found on MaZda web page [35].

Another group of parameters is based on transformations into a profile (holes are removed from a region), into a convex region (concavities are filled in) and skeletonization. Skeletonization is implemented through a thinning algorithm that removes outer pixels of a region to find its medial axis. The result, called a skeleton, preserves information on the region's topology. The skeletal descriptors computed by MaZda are: length of the skeleton, number of branches, branching points and loops, as well as minimal and maximal thickness of the body region surrounding the skeleton.

Such parameters are beneficial in applications where a shape analysis of a given object is necessary. For example, selected geometric parameters were estimated to characterize the morphological structure of skin mast cells [36].

6. Feature reduction

Using MaZda, it is possible to produce a substantial set of features potentially carrying sufficient information for image texture characterization or region classification. However, the achievable number of features computed by MaZda is enormous, reaching a few thousands per region of a color image, and consequently difficult to handle. Several-hundred features mean analysis of a several-hundred-dimensional space. It would be time consuming, inefficient and in some cases not feasible.

Usually only a limited number of features carry relevant information needed for texture discrimination. MaZda allows selection of these features and rejection of the rest. There are four selection methods implemented, all being supervised methods i.e. they require a-priori knowledge which feature vector or sample belongs to which predefined class. Given the information, these methods select a subset of features according to a given mathematical criterion. There are four criteria used in MaZda: Fisher score, classification error combined with the correlation coefficient, mutual information [33, 37] and a selection of optimal feature subsets with minimal classification error of 1-nearest neighbor classifier [38, 39].

Figure 4 shows example of sample distributions in two different feature spaces. Each sample is represented by a digit symbol. The digits indicate the sample membership to the predefined texture class. The first example (Fig. 4. a) shows a feature space of three randomly selected features. The features have no ability for discrimination of the four classes as the samples are mixed together. The second example (Fig. 4. b) shows a feature space of three features selected with one of the automatic methods implemented in MaZda. They satisfy the criterion of the minimal classification error when the nearest neighbor classifier is used. Due to the high discrimination ability of the chosen features, the samples corresponding to particular classes form clear, separate clusters. If the number of selected features is still unacceptably large, it is possible to perform its further reduction by transformation of the original features into a new space with lower dimensionality. This yields a set of new features, reduced in number in comparison to the original feature set. This approach is called feature extraction or projection [40]. Procedures implemented in the b11 module comprise principal component analysis (PCA) [41], linear discriminant analysis (LDA) [42] and nonlinear discriminant analysis (NDA) [39, 42-44].

The two described steps of feature reduction, feature selection and feature projection, lead to a decrease of the feature space dimensionality. This is usually a necessary step before further data analysis, such as classification. None of the implemented methods for feature selection or reduction can be viewed as superior to the others. The choice should be made as a consequence of actual sample distributions and the choice of a classification method to be used. Therefore, the purpose of developing the software is to enable experimenting, verification and choosing the best solution to a given problem under consideration.

7. Texture classification

The b11 module allows visualization of sample distributions within a feature space, statistical analysis of these distributions and classification of feature vectors. It displays clouds of samples presented in one-, two- or three-dimensional space of arbitrarily selected features or within a transformed feature space (Fig. 4 a). Samples of different classes are represented with distinctive symbols. The user can infer the feasibility of classification by determining whether clouds of samples group in separate clusters.

The b11 implements two procedures for nonlinear supervised classification: 1-nearest neighbor (1-NN) classifier and an artificial neural network (ANN). The 1-NN incorporates a simple learning algorithm, in which generalization is performed after collecting all the training data. During the training phase feature vectors and class labels of the training samples are simply stored. In the classification phase, distances from a new sample to all the stored feature vectors are computed, the closest sample is found and a new sample is assigned to the class of the closest sample from the training set. The ANN implemented in b11 is a feed-forward network with two hidden layers of neurons. The neuron's nonlinearity is modeled with a sigmoid function. The number of neurons in the hidden layers is adjustable. The user should prepare two sets of samples, one for training and another for validation. The training procedure fine-tunes neurons for best discrimination of the subsets of the training set. After the training, the resulting net should be validated with the second testing set of samples [42-44]. The resulting net configuration and the results of the training may be stored to a disk file for further use.

The other methods implemented in b11 are useful for unsupervised data classification and cluster analysis [39, 45, 46]. These are the agglomerative hierarchical clustering (AHC) [45, 46], the similarity-based clustering method (SCM) [47] and k-means algorithm [39]. The AHC represents a bottom-up strategy of cluster analysis. The individual samples are at first viewed as separate clusters. The clustering algorithm computes distances between pairs of clusters in feature space. The distance between two clusters characterizes their dissimilarity. Next, the clusters with the lowest dissimilarity are joined together. The process is repeated until a single cluster of samples forms.

The development of AHC can be visualized with a dendrogram (Fig. 5 b), which is a hierarchical tree. The tree leaves represent individual samples whereas the branches represent links between samples or clusters. The level, at which branches join, represents dissimilarity between the joined clusters. The user can adjust the clustering result in two ways: by selecting one of four available dissimilarity measures and by defining the dissimilarity level at which the dendrogram is split into clusters (sub-trees).

The SCM defines a continuous, parameterized similarity function, which corresponds to the density of samples within the feature space. The number of the local maxima of function determines the number of clusters. Each individual sample is iteratively relocated within the feature space by the function's gradient. Eventually, samples reach locations of certain maxima of the function, which in turn determine their membership to the corresponding clusters. The user can control the result of clustering by adjusting the similarity function parameter, which is responsible for the smoothness and the number of maxima of the function.

The third clustering method implemented in b11 utilizes a k-means algorithm. The algorithm separates samples into a predefined number of k clusters by minimizing the total sum of distances between samples and centers of clusters they are assigned to. To verify the result of clustering with the k-means algorithm, the user can examine average silhouette [48] plots or the silhouette value. There are as many plots as there are clusters. Plots that resemble a rectangle indicate accurate clustering.

8. Feature maps and image segmentation

As already mentioned, MaZda also computes feature distributions within the image (feature maps). Each point of a map represents a particular textural feature value that corresponds to a given point of a textured image. The map is represented by a grey-scale image, in which a textural feature value is depicted by a relative gray level. The feature at a given image location is computed within a rectangular region (a mask) centered at this location. The mask slides over the image surface by a given vertical and horizontal step in order to fill the whole output image with computed feature values. The user can select features for which maps should be computed, height and width of the mask and the horizontal and vertical steps.

Segmentation is an image processing task that partitions the image into separate regions, which are in some way homogeneous. The most common segmentation routine is performed through image gray level thresholding. In this method, image pixels of intensity higher then the threshold level fall into one region, the others fall into the other. Unfortunately, if the goal is to segment a texture, the image gray level thresholding alone usually fails. Nevertheless, the thresholding can still be effective if preceded by a feature map computation. If the feature discriminates two different textures, and then the feature map is computed on an image containing such textures, the result would be an image showing one texture as a dark area and the other one as a bright area. Therefore, thresholding the brightness of the feature map would separate the two textures visible in the input image. A visual inspection of maps produced by MaZda allows determining which feature maps can be used for texture segmentation.

To study the feasibility of image texture segmentation based on multiple feature maps, an unsupervised method of k-means clustering was implemented in b11 module. The MaZda user can load a number of arbitrary selected feature maps, then enter the number of segments or texture classes present in the image and run the segmentation algorithm. The result is an image that represents individual texture regions with unique colors.

Figure 6 shows an example of texture image segmentation by means of feature maps. The input image consists of two different artificially generated textures. These textures are hardly distinguished by a human eye. Moreover, they cannot be immediately segmented by simple image segmentation methods such as grey-level thresholding. MaZda introduces an intermediate step of image conversion – it computes feature maps. After that, the image segmentation becomes feasible with feature map grey-level thresholding or segmentation tools implemented in b11.

9. Applications

Since patterns or texture areas appear in almost all biomedical images they can be investigated with textural analysis tools, such as MaZda. The software was already utilized in many domains including MRI measurement protocol optimization, various medical studies, food quality studies and others.

Within the COST B11 and B21 projects several studies on MRI scanning protocols were carried out. To assure the quality and provide means for MRI scanner calibration, test objects [3] (phantoms) are used. Such phantoms imitate characteristics of living tissues and are visualized with different MRI scanners to produce test images. The images serve for quality control of scanners, their testing and for standardization of protocols. The phantoms' images obtained in various medical centers over several years were evaluated and compared using MaZda program. These studies show phantoms usefulness for scanner quality testing and the phantoms' invariability in time when used for scanner calibration.

MaZda was also applied to identify and discriminate biomedical image areas with different textural characteristics, such as those that represent healthy and pathological tissues.

Example studies involved early detection of osteoporotic changes in bones [4-6], detection of amygdale activation in rat brains [7], detection and quantification of hipocampal sclerosis [8], distinguishing between brain tumors [3], discrimination of healthy and cirrhotic livers [9], textural analysis of trabecular bone images targeted at osteoporosis detection [10, 11], monitoring of atrophy and regeneration of muscles [12], monitoring of teeth implants [13], analysis of myocardium tissue in ultrasound images [14], assessment of cellular necrosis in epithelial cell [15] and evaluation of anti-vascular therapy of mammary carcinomas in mice [16].

Figure 7 presents results of forearm bone X-ray images analysis [4]. There are three classes of images, healthy, osteopenic and osteoporotic bones, 9 images per class. The procedure of textural features computation, feature selection and feature reduction enabled determination of the two most discriminative features (MDF) by means of linear discriminant analysis. In the presented case, the obtained features allow errorless differentiation between the three image classes.

Texture analysis is useful not only in medicine. Application of such analysis to agriculture and food processing industry leads to fruitful results. MaZda tools turned out to be useful in discrimination between potato varieties, cooked and raw potatoes [18], analysis of the influence of apple ripening process on storage [19], and assessment of soft cheese quality [17]. More examples related to MaZda applications can be found in [3].

Figure 8 presents results of potato image analysis. Potato samples belonging to four potato varieties were examined with a magnetic resonance imaging scanner. The obtained images were analyzed with MaZda package. The procedure of textural features computation and feature selection led to the conclusion that the examined potato varieties have dissimilar structure of storage parenchyma, which results in significant between-classes differences of a certain set of textural features. The sample distributions in Fig. 8 show that samples belonging to different potato varieties tend to group in specific areas of textural feature space.

10. Conclusions

MaZda package is an efficient and reliable set of tools for analysis of image textures. Its efficiency was confirmed by the participants of the COST B11 and B21 projects and other researchers who applied this software for many different texture analysis tasks. The methods implemented in MaZda and b11 were carefully selected to be useful for 2D and 3D image analysis applications. The software implies a functional sequence of actions to perform while the choice of such a sequence is not an obvious solution.

Compared to other texture analysis software, like Keyres [22] or LS2W [23], it provides a complete analysis path for texture images, including feature estimation, statistical analysis of feature vectors, classification and image segmentation. Additional information which includes the list of features produced by MaZda, the list of script instructions, tutorials, the manual and executable code is available on the web page [35] of the Institute of Electronics, Technical University of Łódź.

Acknowledgments

This work was performed within the framework of COST B21 European project: "Physiological Modeling of MR Image Formation". The authors would like to thank Michael

Friedlinger, Marcin Kociolek and Slawomir Razniewski for their contribution to the development of MaZda.

References

[1] A. Materka, M. Strzelecki, Texture Analysis Methods – A Review, Technical University of Lodz, Institute of Electronics, COST B11 report, Brussels 1998, (http://www.eletel.p.lodz.pl/programy/cost/pdf_1.pdf).

[2] I.-M. Sintorn, M. Homman-Loudiyi, C. Söderberg-Nauclér, G. Borgefors, A refined circular template matching method for classification of human cytomegalovirus capsids in TEM images, Computer Methods and Programs in Biomedicine, 76 (2004) 95-102.

[3] Texture Analysis for Magnetic Resonance Imaging, (eds. M. Hajek, M. Dezortova, A. Materka, R. Lerski), Med4publishing, Prague, 2006.

[4] M. Cichy, A. Materka, J. Tuliszkiewicz, Computerised Analysis of X-ray Images for Early Detection of Osteoporotic Changes in the Bone, Proc. Conf. Information Technology in Medicine TIM '97, Jaszowiec, Poland, 1997, pp. 53-61.

[5] A. Materka, P. Cichy, J. Tuliszkiewicz, Texture analysis of X-ray images for detection of changes in bone mass and structure, in: Pietikainen M. K. (Ed.), Texture Analysis in Machine Vision, Series in Machine Perception & Machine Intelligence, World Scientific, 40 (2000) 189-195.

[6] S. Blouin, M.F. Moreau, M.F. Baslé, D. Chappard, Relations between Radiograph Texture Analysis and Microcomputed Tomography in Two Rat Models of Bone Metastases, Cells, Tissues, Organs, 182 (3-4) (2006) 182-192.

[7] O. Yu, N. Parizel, L. Pain, B. Guignard, B. Eclancher, Y. Mauss, D. Grucker, Texture analysis of brain MRI evidences the amygdala activation by nociceptive stimuli under deep anesthesia in the propofol–formalin rat model, Magnetic Resonance Imaging, 25 (1) (2007) 144-146.

[8] L. Bonilha, E. Kobayashi, G. Castellano, G. Coelho, E. Tinois, F. Cendes, L. M. Li, Texture Analysis of Hippocampal Sclerosis, Epilepsia, 44 (12) (2003) 1546–1550.

[9] D. Jirák, M. Dezortová, P. Taimr, M. Hájek, Texture analysis of human liver, Journal of Magnetic Resonance Imaging, 15 (1) (2002) 68–74.

[10] E. Lerouxel, H. Libouban, MF. Moreau, MF. Baslé, M. Audran, D. Chappard, Mandibular bone loss in an animal model of male osteoporosis (orchidectomized rat): a radiographic and densitometric study, Journal Osteoporosis International, Springer, 15 (10) (2004) 814-819.

[11] S. Herlidou, R. Grebe, F. Grados, N. Leuyer, P. Fardellone and M.-E. Meyer, Influence of age and osteoporosis on calcaneus trabecular bone structure: a preliminary in vivo MRI study by quantitative texture analysis, Elsevier, Magnetic Resonance Imaging, 22 (2) (2004) 237-243.

[12] D. Mahmoud-Ghoneim, Y. Cherel, L. Lemaire, J. D. de Certaines, A. Manier, Texture analysis of magnetic resonance images of rat muscles during atrophy and regeneration, Magnetic Resonance Imaging, 24 (2) (2006) 167-171.

[13] M. Kozakiewicz, M. Stefanczyk, A. Materka, P. Arkuszewski, Selected Characteristic Features of Radiotexture of Bone of the Dental Alveolus in the Human Maxilla and Mandible, Magazyn Stomatologiczny, 3 (2007) 40-43 (in Polish).

[14] V. Punys, J. Puniene, R. Jurkevicius, J. Punys, Myocardium Tissue Analysis Based on Textures in Ultrasound Images, Studies in Health Technology and Informatics, 116 (2005) 435-440.

[15] A. Santos, C. Ramiro, M. Desco, N. Malpica, A. Tejedor, A. Torres, M. J. Ledesma-Carbayo, M. Castilla, P. García-Barreno, Automatic detection of cellular necrosis in epithelial cell cultures, Medical Imaging 2001, M. Sonka, K.M. Hanson (eds.). Proceedings of SPIE, 4322, 2001, pp. 1836-1844.

[16] G. Chen, S. Jespersen, M. Pedersen, Q. Pang, MR. Horsman, H. Stødkilde-Jørgensen, Evaluation of anti-vascular therapy with texture analysis, Anticancer Res., 25 (5) (2005) 3399-3405.

[17] G. Collewet, M. Strzelecki, F. Mariette, Influence of MRI acquisition protocols and image intensity normalization methods on texture classification, Magnetic Resonance Imaging, 22 (2004) 81-91.

[18] A.K. Thybo, P.M. Szczypinski, A.H. Karlsson, S. Donstrup, H. Stodkilde-Jorgensen, H.J. Andersen, Prediction of sensory texture quality attributes of cooked potatoes by NMR-imaging (MRI) of raw potatoes in combination with different image analysis methods, Journal of Food Engineering, 61 (1) (2004) 91-100.

[19] J. Letal, D. Jirak, L. Suderlova, M. Hajek, MRI texture analysis of MR images of apples during ripening and storage, Lebensmittel-Wissenschaft und -Technologie, 36 (7) (2003) 719-727.

[20] J. Racz, A.Dubrawski, B. Siemiatkowska, M. Nieniewski, Computer-Aided Diagnosis of Breast Cancer Based on Analysis of Microcalcifications, Proceedings of 5th International Workshop on Digital Mammography, June 2000, Toronto, Canada, Medical Physics Publishing Madison.
[21] M. Friedlinger, L.R. Schad, S. Bliiml, B. Tritsch, W.J. Lorenz, Rapid automatic brain volumetry on the basis of multispectral 3D MR imaging data on personal computers. Comput. Med. Imaging Graph. 19 (1995) 185-205.
[22] http://www.keyres-technologies.com (visited: March 2008).
[23] http://www.maths.bris.ac.uk/~wavethresh/LS2W (visited: March 2008).
[24] G.P. Nason, B.W. Silverman, The Stationary Wavelet Transform and some Statistical Applications, Antoniadis and G. Oppenheim, eds., Springer-Verlag. New York (1995) 281-299.
[25] P.M. Szczypinski, Center Point Model of Deformable Surface, ICCVG, Warsaw, Poland, September 2004, Springer, Computational Imaging and Vision, 32 (2006) 343-348.
[26] P.M. Szczypinski, M. Strzelecki, A. Materka, MaZda – a Software for Texture Analysis, Proc. of ISITC 2007, November 23-23, 2007, Jeonju, Korea, pp. 245-249.
[27] L. Cohen, Time-frequency distributions, Proc. IEEE, 77 (7) (1989) 941-981.
[28] A.C. Bovik, M. Clark, W.S. Geisler, Multichannel texture analysis using localized spatial filters, IEEE Trans. Pattern Analysis and Machine Intelligence, 12 (1) (1990) 55-73.
[29] J.G. Daugman, Complete Discrete 2-D Gabor Transforms by Neural Networks for Image Analysis and Compression, IEEE Trans. Acoustic, Speech, Signal Processing, 36 (7) (1988) 1169-1179.
[30] A. Jain, Fundamentals of Digital Image Processing, Prentice-Hall International, Englewood Cliffs, 1989.
[31] S.G. Mallat, Multifrequency channel decompositions of images and wavelet models, Acoustics, Speech, and Signal Processing, IEEE Transactions on, 37 (12) (1989) 2091-2110.
[32] R. Haralick, Statistical and Structural Approaches to Texture, Proc. IEEE, 67 (5) (1979) 786-804.
[33] A. Materka, M. Strzelecki, P. Szczypiński, MaZda manual, 2006 (available at [1]).
[34] D.W. Luerkens, Theory and Application of Morphological Analysis: Fine Particles and Surfaces, 1991, CRC Press (http://books.google.com).
[35] http://www.eletel.p.lodz.pl/mazda (visited: March 2008).
[36] M. Strzelecki, H. Kim, P. Liberski, A. Zalewska, Analysis of microscopic mast cell images based on network of synchronised oscillators, Adaptive and Natural Computing Algorithms (eds. B. Bieliczynski, A. Dzielinski, M. Iwanowski, B. Ribeiro), Proc. of ICANNGA 2007, Warsaw, Poland, Springer LNCS 2007, pp. 346-35.
[37] G.D. Tourassi, E.D. Frederick, M.K. Markey, C.E. Floyd, Jr. Application of the mutual information criterion for feature selection in computer-aided diagnosis, Medical Physics, 28 (12) (2001) 2394-2402.
[38] M. Dash, H. Liu, Feature Selection for Classification, Intelligent Data Analysis, 1 (3) (1997) 131-156.
[39] R. Duda, P.E. Hart, D.G. Stork, Pattern Classification (2nd Edition), John Wiley & Sons, New York, 2001.
[40] A.K. Jain, R.P.W. Duin, J Mao, Statistical Pattern Recognition: A Review. IEEE Trans. Pattern Anal. Mach. Intell. 22 (1) (2000) 4-37.
[41] W. Krzanowski, Principles of Multivariable Data Analysis, Oxford University Press, 1988.
[42] K. Fukunaga, “Introduction to Statistical Pattern Recognition”, Academic Press, New York, 1991.
[43] J. Mao, A. Jain, “Artificial Neural Networks for Feature Extraction and Multivariate Data Projection” IEEE Trans. Neural Networks, 6 (1995) 296-316.
[44] R. Hecht-Nielsen, „Neurocomputing“, Addison-Wesley, 1989.
[45] A. Jain, R. Dubes, Algorithms for Clustering Data, Prentice Hall, 1998.
[46] A.K.Jain, M.N. Murty, P.J. Flynn, Data clustering: a review, ACM Computing Survey, 31 (3) (1999) 264-323.
[47] M. Yang, K. Wu, A Similarity-Based Robust Clustering Method, IEEE Trans. on Pattern Analysis and Machine Intelligence, 24 (4) (2004) 434-448.
[48] A. Struyf, M. Hubert, P.J. Rousseeuw, Integrating robust clustering techniques in S-PLUS, Computational Statistics & Data Analysis, 26 (1997) 17-37.

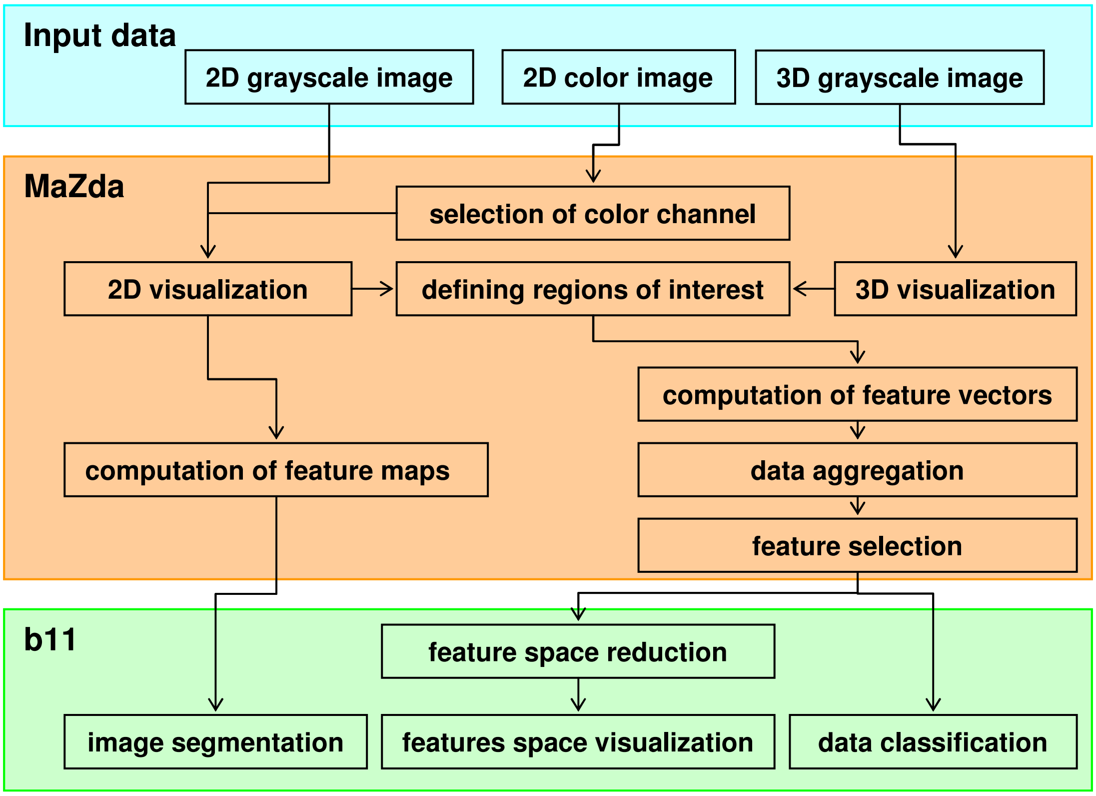


Fig. 1. Flowchart of analysis pathways in MaZda/b11 package

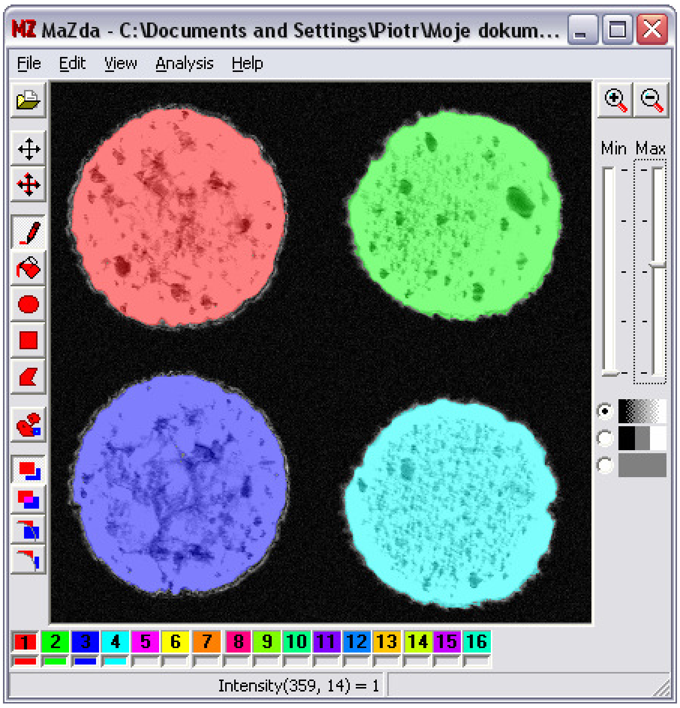


Fig. 2.a

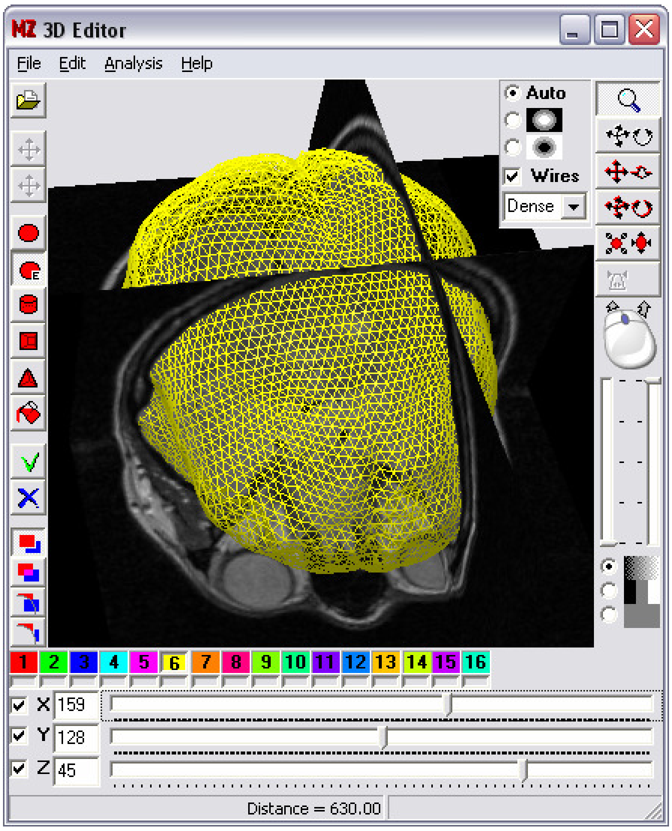
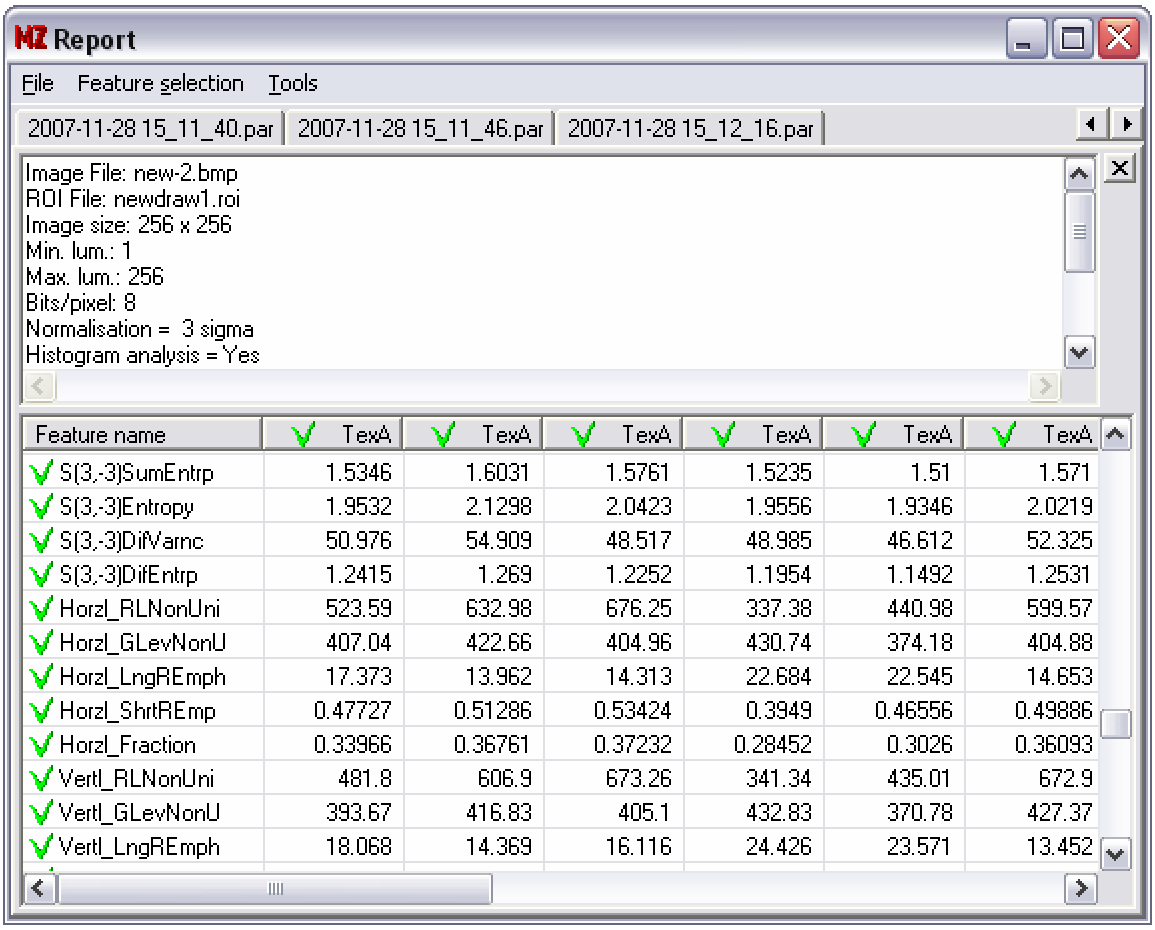


Fig. 2.b

Fig. 2. Region of interest editors: a) 2D ROI editor with an MRI image of cheeses and b) 3D ROI editor with human head volumetric data (a deformable surface net detecting brain boundary)



Feature name	TexA	TexA	TexA	TexA	TexA	TexA
S(3,-3)SumEntrp	1.5346	1.6031	1.5761	1.5235	1.51	1.571
S(3,-3)Entropy	1.9532	2.1298	2.0423	1.9556	1.9346	2.0219
S(3,-3)DifVarnc	50.976	54.909	48.517	48.985	46.612	52.325
S(3,-3)DifEntrp	1.2415	1.269	1.2252	1.1954	1.1492	1.2531
Horzl_RLNonUni	523.59	632.98	676.25	337.38	440.98	599.57
Horzl_GLevNonU	407.04	422.66	404.96	430.74	374.18	404.88
Horzl_LngREmph	17.373	13.962	14.313	22.684	22.545	14.653
Horzl_ShrtREmp	0.47727	0.51286	0.53424	0.3949	0.46556	0.49886
Horzl_Fraction	0.33966	0.36761	0.37232	0.28452	0.3026	0.36093
Vertl_RLNonUni	481.8	606.9	673.26	341.34	435.01	672.9
Vertl_GLevNonU	393.67	416.83	405.1	432.83	370.78	427.37
Vertl_LngREmph	18.068	14.369	16.116	24.426	23.571	13.452

Fig. 3. The report window of MaZda

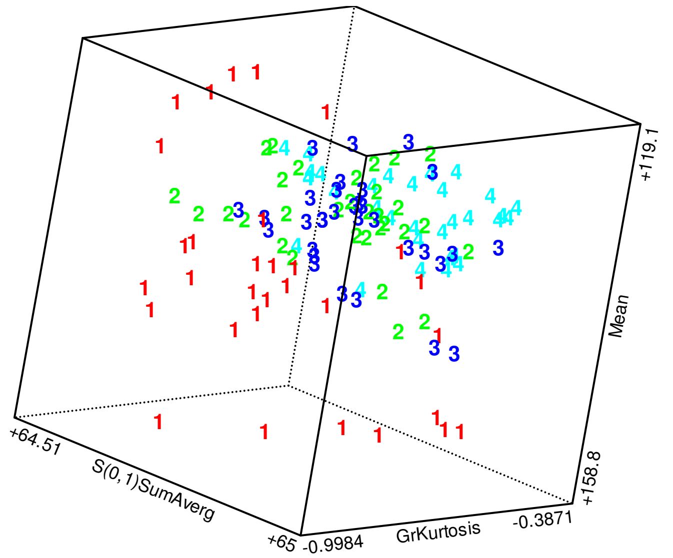


Fig. 4.a

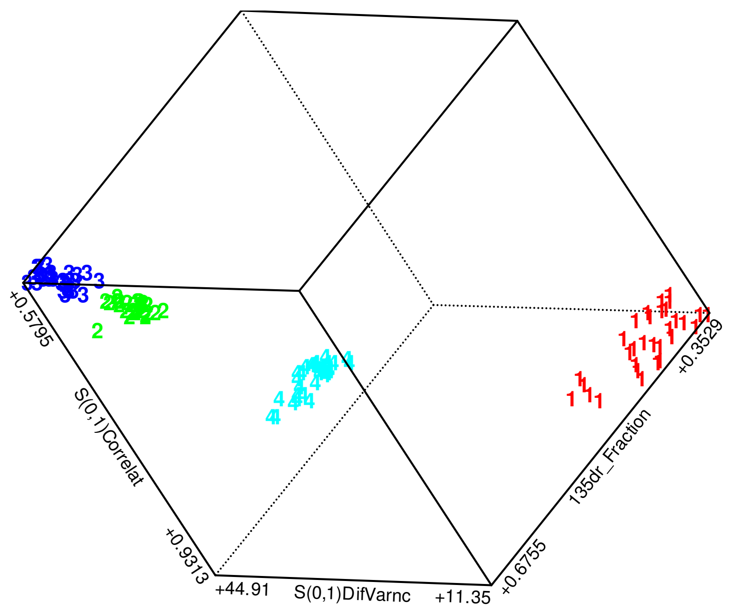


Fig. 4.b

Fig. 4. Sample distributions visualized in 3D feature space: a) randomly selected features and b) features selected with the minimal classification error of the nearest neighbor classifier

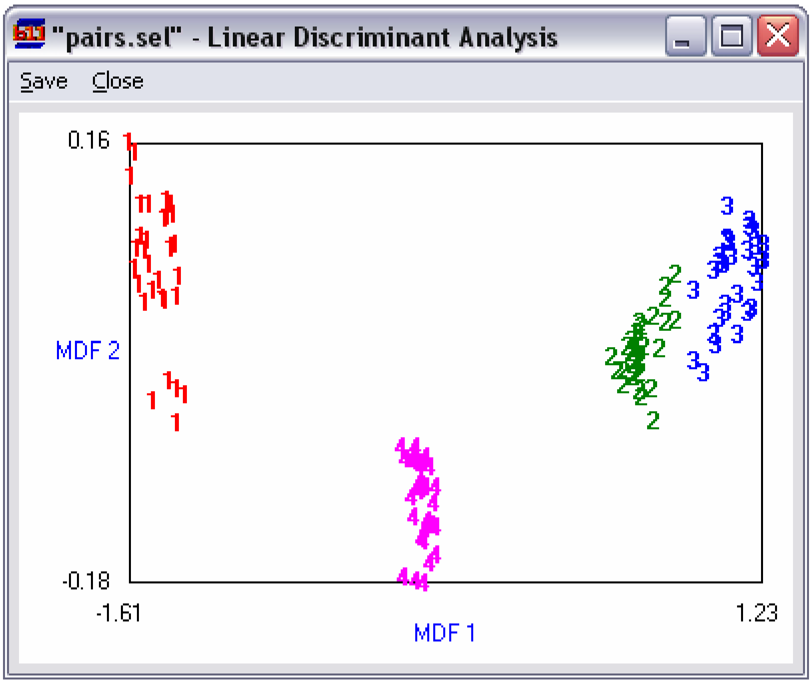


Fig. 5.a

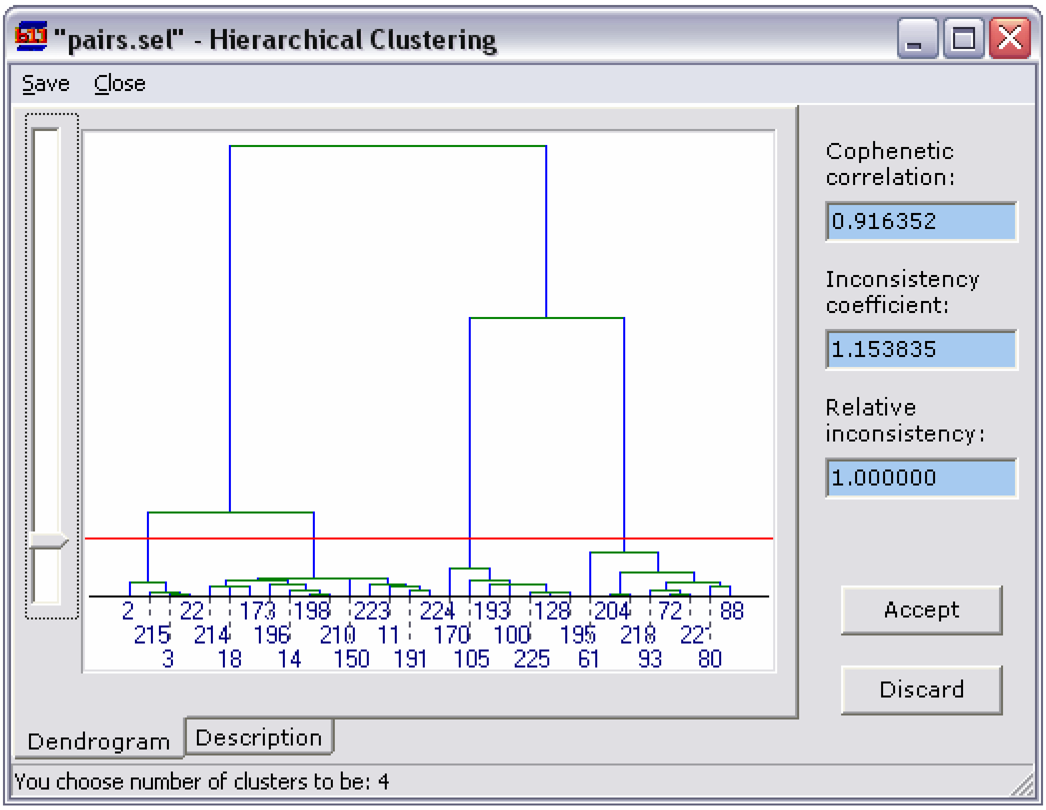


Fig. 5.b

Fig. 5. Samples' distributions after the linear discriminant analysis (a) and dendrogram of agglomerative hierarchical clustering (b)

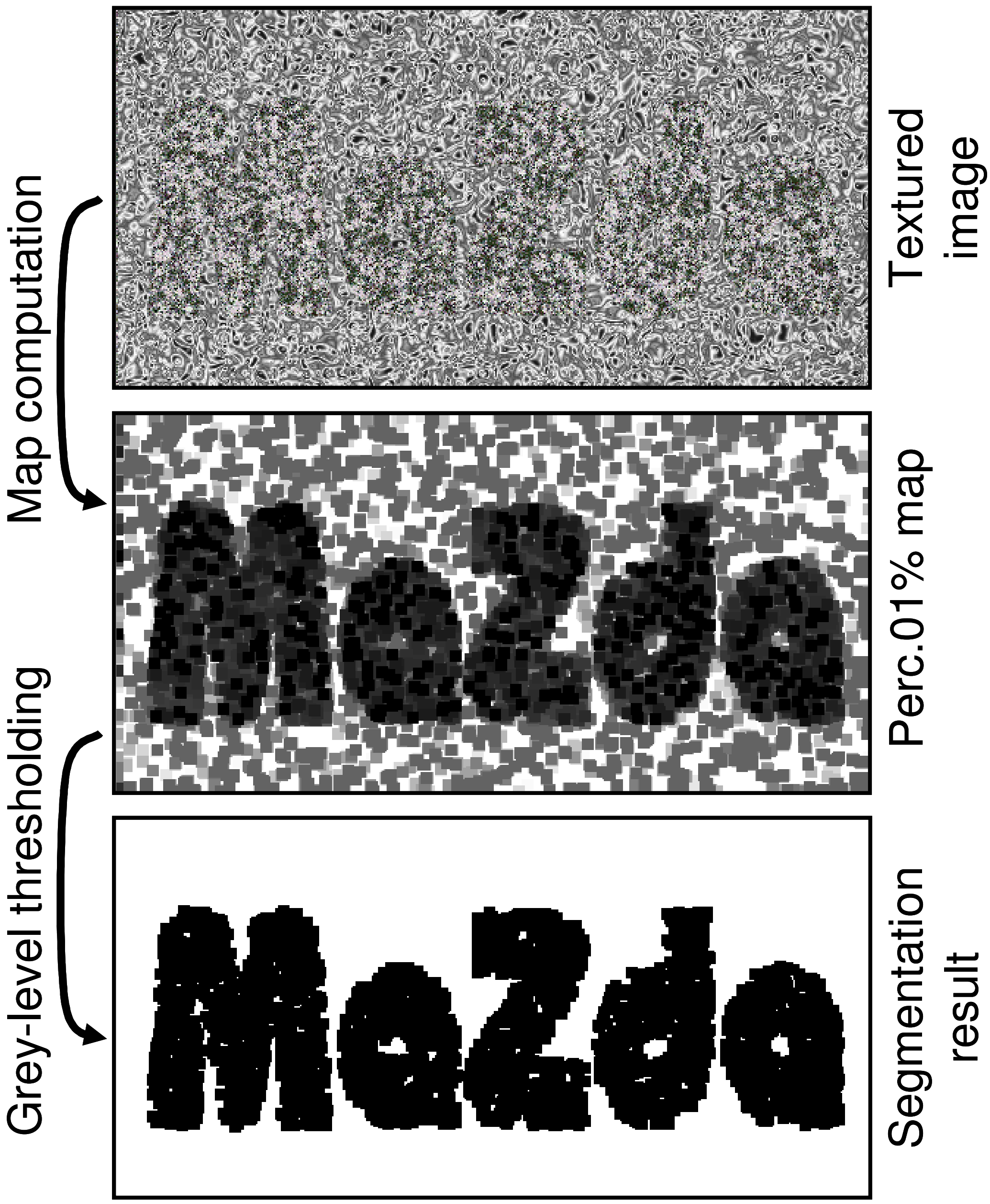

Textured image
Perc.01% map
Segmentation result
Map computation
Grey-level thresholding

Fig. 6.a

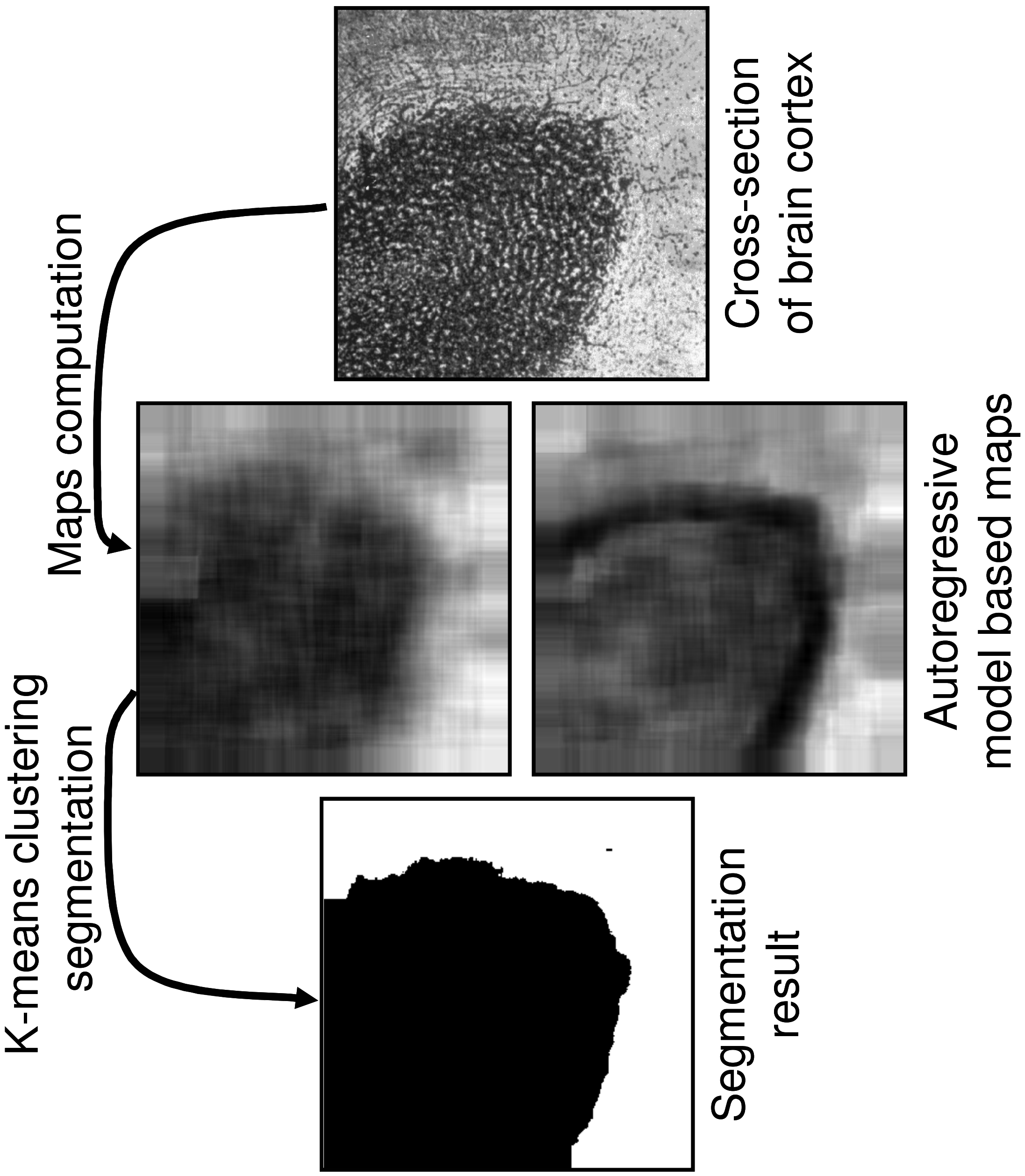


Fig. 6.b

Fig. 6. Illustration of the textured image segmentation procedure by means of texture feature maps: a) artificially created image and b) MRI cross-section of brain cortex

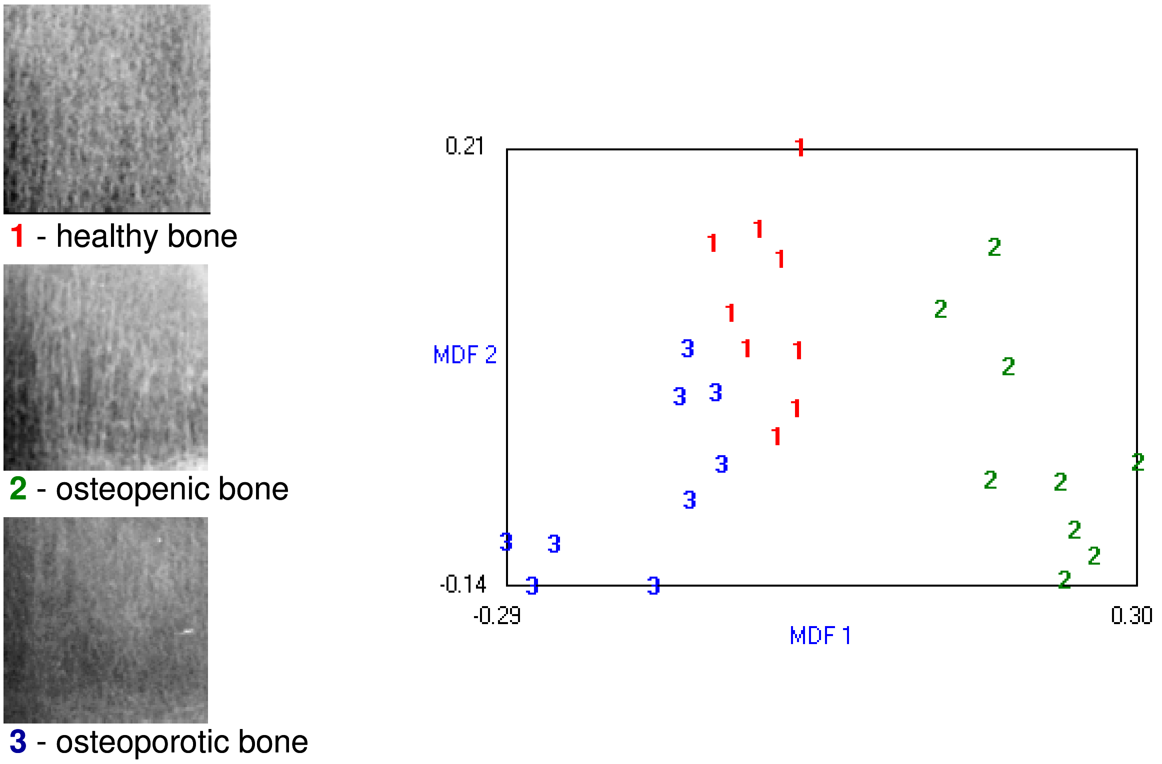


Fig. 7. Example forearm bone X-ray images [4] and their sample distributions after linear discriminant analysis

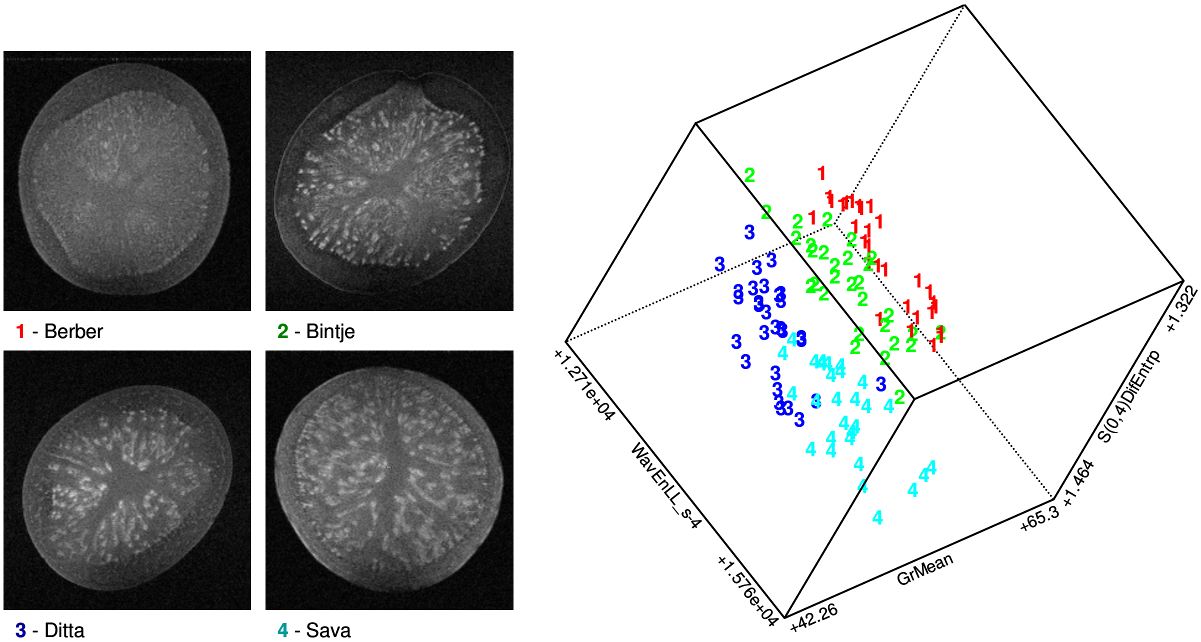


Fig. 8. Example of four potato varieties MRI scans and their sample distributions in space of three selected, most discriminative features