MAZDA – THE SOFTWARE PACKAGE FOR TEXTURAL ANALYSIS OF BIOMEDICAL IMAGES

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 *– A MaZda software package for 2D and 3D image texture analysis is presented. The software was written to compute a variety of textural features within arbitrarily shaped regions of interest. It also includes procedures for statistical analysis of computed feature sets, to aid in image classification and image content recognition. The software was used for research within framework of COST B11 and COST B21 multi-center international projects and it has proven to be an efficient tool for quantitative analysis of magnetic resonance images (MRI) – an aid to more accurate and objective medical diagnosis.*

1. Introduction

The texture as perceived by humans is a visualization of complex patterns composed of spatially organized, repeated subpatterns, which have characteristic somewhat uniform appearance [27]. The local subpatterns within an image are perceived to demonstrate specific brightness, color size, roughness, directivity, randomness, smoothness, granulation, etc. The texture may carry substantial information about the structure of physical objects. Thus, the textural image analysis is an important issue in image processing and understanding.

Although image texture is easily perceived by humans, we still lack a strict definition what exactly the texture is. Therefore, the process of texture analysis is in many cases somewhat intuitive, and results of such analysis are rarely predictable. To aid in textural analysis computer programs, such as MaZda, may be beneficial. The MaZda software was already utilized [19, 23] in many areas including MRI measurement protocol optimization, various medical studies, food quality studies, et caetera.

At the beginning of 1998, the European COST B11 project started. One of the objectives of the project was development of quantitative textural analysis methods of magnetic resonance images. At that time there was no commercially available software capable of quantitative analysis of texture within freely selected regions of interest (ROI) and interpretation of computed results. MaZda was the first program created to satisfy this objective. In fact, its development started two years before, as it was a program for texture analysis in mammogram images. The early version of MaZda computed textural features derived from co-occurrence matrix, which is Macierz Zdarzen in Polish. Hence the name of the software is an abbreviation of Macierz Zdarzen. In 1998, several procedures implemented in NMRWin program developed 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. Throughout the last ten years MaZda was continuously enhanced and expanded with further functionality including color and 3D image analysis, 2D and 3D image segmentation, data classification, analysis automation and others.

The program code has been written in C++ and Delphi™ with 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 statistical and discriminative analysis). The MaZda package is widely used by participants of COST B11 and successive B21 projects, by other collaborating scientists and students in numerous research areas. Further sections describe program functionality along with examples of selected applications.

2. Image analysis pathways in MaZda

There are several pathways of image analysis that can be handled by the MaZda package (Fig. 1). Starting with 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. Then, user is given a choice between analyzing the image as a whole or analyzing image within 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 can be useful for image segmentation, as the feature vectors for classification of image content.

Feature vectors computed by MaZda may include up to several hundred features per individual region of interest. Such a number of features, creating several-hundred-dimensional spaces, are not easy to handle by statistical analysis or by classifiers implemented in b11. 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, which use various selection criteria, which can be chosen by the MaZda user.

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

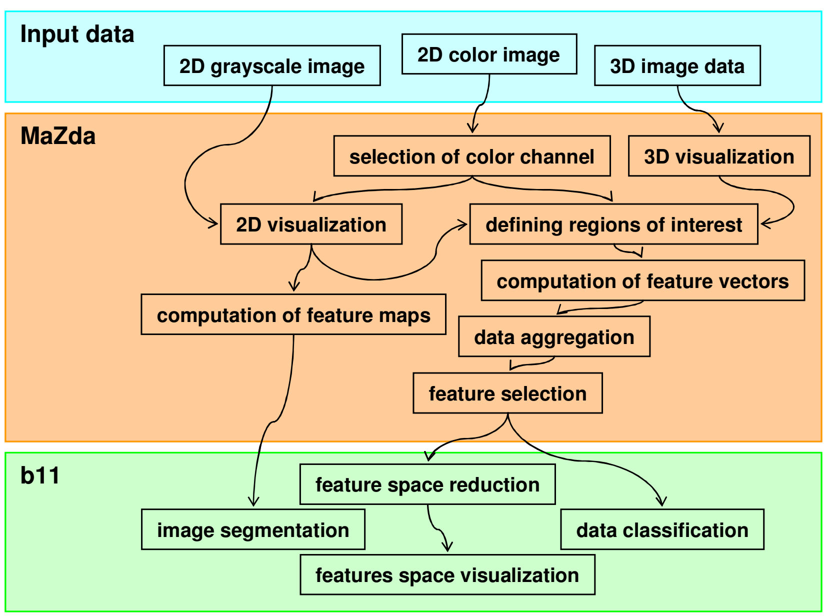

Fig. 1. Flowchart of analysis pathways in MaZda/b11 package

3. Textural features

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

There are three categories of feature extraction approaches that MaZda includes: statistical, model-based and image transform. Statistical approaches represent the texture indirectly by the non-deterministic properties that govern the distributions and relationships between the grey levels of an image. Model based texture analysis [27], using fractal or stochastic models, attempt to interpret an image texture by use of generative image models and stochastic models respectively. Transform methods of texture analysis, such as Fourier, Gabor or wavelet transforms [28] represent an image in a space whose co-ordinate system has an interpretation that is related to the characteristics of a texture.

The user of MaZda package, by means of Options window controls, may select which group of features to generate. At choice are histogram, gradient, co-ocurrence matrix, run-length matrix, autoregressive model [27] and Haar wavelet [25] groups of features.

The most common, statistical method for image features extraction is based on image first-order histogram. The histogram is computed from pixels' intensity, 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, skewnes, kurtosis and percentiles. Another statistical method derives features from the image gradient's magnitude map. In similar way to the image histogram features, the histogram of the image gradient is computed and statistical parameters of such a histogram distribution are determined.

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, and they demonstrate statistics, such as angular second moment, contrast, correlation, sum of squares, and various averages, variances, inverse moments and entropies [30].

The run-length matrix (RLM) holds counts of pixel runs, having 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 [30].

There are also model-based textural features computed by the software, which are based on autoregressive model of image. The model assumes that pixel intensity, in reference to the mean value of image intensity, can 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 the fifth parameter which is a variance of a minimized prediction error.

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

To make sure the features characterize image texture exclusively and do not depend on some global image characteristics like overall brightness or image contrast, caused e.g. by varied illumination or some other biasing, the normalization procedure has been implemented. The normalization removes 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 mean luminance in the middle and span of 3 standard deviations, onto a white-to-black gray-scale range. The other remaps an image histogram in a range between the first and ninety ninth percentile onto white-to-black range. The image normalization step is performed prior to textural features computation.

The other image transformation that precedes features computation, and influences the way features are computed, 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 set-up substantially changes lengths of pixels in runs and size of the co-occurrence matrix, which in result affect the time and results of computation based on RLM and COM matrices, respectively.

Summarizing, the Mazda software allows for computation of 9 histogram-based textural features, 11 co-occurrence-matrix-based, 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, 5 based on autoregressive model and up to 20 based on Haar wavelet transform. Altogether 279 numbers, which can characterize a grey-scale image texture. All the features can be computed within the image of original histogram or within the image with normalized histogram, at various setups of bit per pixel option.

Methods for textural features computation implemented in MaZda require a gray-scale image as an input. On the other hand, it is evident that often color in color images carries essential information required for image differentiation or image recognition. In MaZda, it may be chosen to analyze 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 get comprehensive characterization of color texture.

4. Regions of interest

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

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

ROIs may be loaded from a disk file or defined with MaZda ROI editors. To edit 2D ROIs (Fig. 2 a), drawing tools such as pencil, draw line (with various line thickness), draw square, rectangle, circle, ellipsis are used. Also tools based on image grey level thresholding and flood-filling are available. In addition, to process a region shape, tools based on morphological transformations can be used, 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).

a) b)

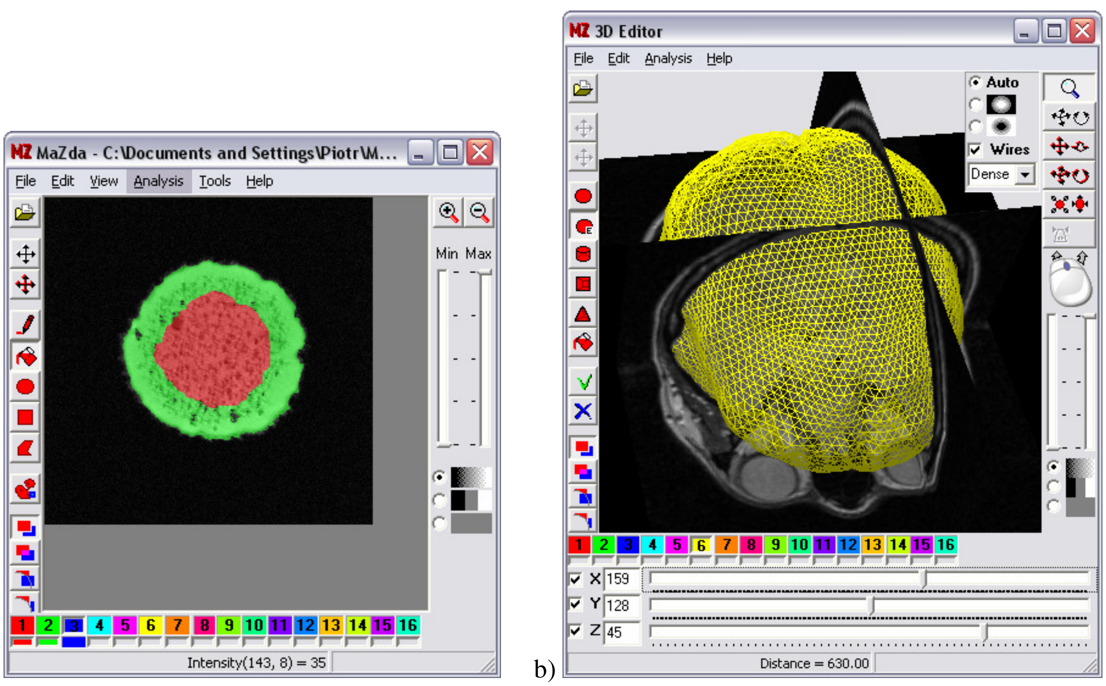

Fig. 2. Region of interest editors: a) 2D ROI editor with a cheese image example and b) 3D ROI editor with human head volumetric data (deformable surface net detecting brain boundaries presented)

Volumetric ROIs within 3D (Fig. 2 b) images, e.g. images from magnetic resonance or computer tomography scanners, can be defined with other set of tools. The simplest way is to assemble ROI from predefined blocks, such as sphere, tube, cube and tetrahedron. Blocks can be placed within 3D image space at chosen location. The orientation, size and proportions of blocks can be adjusted freely. Other ways to create 3D ROI are to perform image segmentation with image grey-level thresholding and flood-filling, or to edit regions cross-section with the 2D ROI editing tools. The most advanced tool for 3D region editing implemented in MaZda is deformable surface [26]. It is a mathematical model of enclosed surface that starts from 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 selected threshold value. The final shape of the model strongly depends on initial shape and location of the surface, image contrast and some other parameters. Therefore, the deformable surface is implemented as an interactive tool allowing the user to adjust these parameters, to get the most satisfying shape.

5. Geometric parameters

Two-dimensional regions of interest, which were primarily planned as masks for textural analysis, may be also viewed as images themselves. They represent silhouettes of two-dimensional objects that hey cover and they may carry key information for classification of such objects. Therefore, another approach for feature extraction [28] is to measure characteristics of these regions, such as location, orientation, size, geometric and topology descriptors, etc. The software computes parameters such as areas, perimeters, various diameters and radix, including Feret's and Martin's, as well as parameters of inscribed circle, circumscribed circle, ellipsis, rectangle and various ratios of these parameters. Most of such ratios are size invariant as elongation, compactness or roundness. Other parameters implemented in the software that are size invariant are first and second order binary moments.

Other group of parameters are based on transformations into a profile (wholes are removed from 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 a medial axis of the region. A result, called a skeleton, preserves information on region's topology. The skeletal descriptors computed by MaZda are: length of a skeleton, number of branches, branching points and loops, as well as minimal and maximal thickness of a region body surrounding the skeleton.

6. Feature selection and reduction

Using MaZda, one can produce a substantial set of features potentially carrying sufficient information for image texture characterization or region classification. On the other hand, the possible number of features computed by MaZda is enormous, may reach a few thousands per region of color image, and is difficult to handle. The several-hundred features turns into the problem of analysis of a several-hundred-dimensional space. This would be time consuming, inefficient or even not feasible.

Usually only a limited number of features carry relevant information needed for texture discrimination. MaZda allows for selection of these most effective ones and rejection of the others. There are four methods for feature selection implemented. These are supervised methods i.e. they require a-priori knowledge on 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 coefficient, classification error combined with correlation coefficient, mutual information and selection of optimal feature subsets with minimal classification error of 1-nearest neighbor classifier.

If the number of selected features is still unacceptably large, it is possible to perform their further reduction by transformation of the original features to a new space with lower dimensionality. This approach is called feature reduction or projection. Procedures implemented in the b11 module comprise principal component analysis (PCA), linear discriminant analysis (LDA) and nonlinear discriminant analysis (NDA) [5].

The two described steps, feature selection and feature reduction, lead to decrease of feature space dimensionality. This is usually a necessary step before further data analysis, like 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 classification method to be used. Therefore, the purpose of developing the software is to allow for experimenting, verification and choosing the best solution to a problem being considered.

7. Texture classification

The b11 allows visualization for viewing 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 arbitrary selected features or within the transformed feature space (Fig. 3 a). Samples of different classes are represented with distinctive symbols. The user may conclude about feasibility of classification by determining whether clouds of samples group in separate clusters.

The b11 implements two procedures for nonlinear supervised classification: 1-nearest neighbors (1-NN) classifier and artificial neural network (ANN). The 1-NN incorporates a simple learning algorithm, in which generalization is done 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 the new sample to all stored feature vectors are computed, k closest samples are selected and the new sample is assigned to the most numerous class within the k-samples set. The ANN implemented in b11 is a feed-forward network with two hidden layers of neurons. The neuron's nonlinearity is modeled with sigmoid function. The number of neurons in the hidden layers is adjustable. The user should prepare two sets of samples, one for training the other 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 another, testing set of samples. The resulting net configuration and result of training may be stored to a disk file for further use.

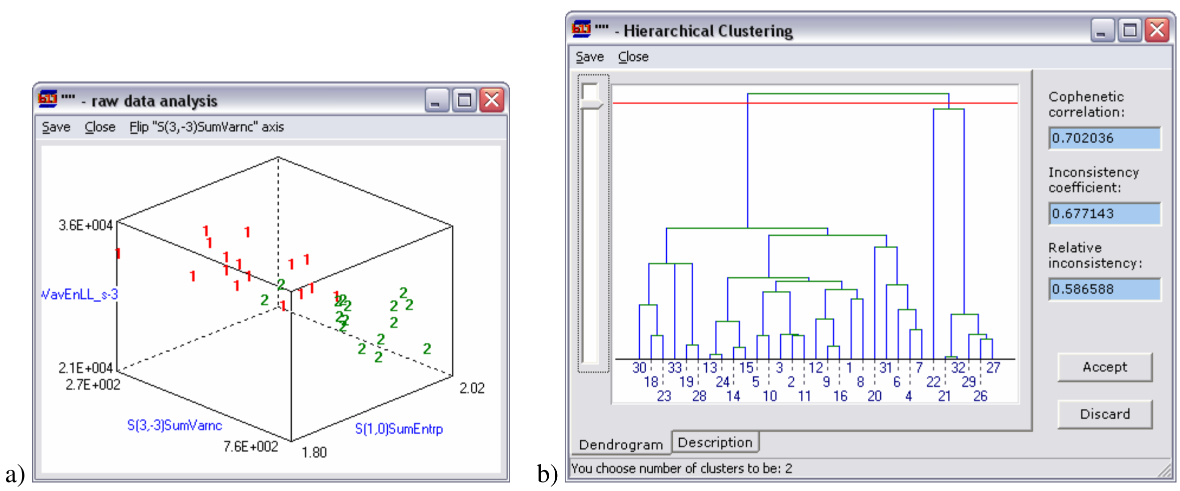

Fig. 3. Feature distribution analysis and data clustering in b11:
a) sample distributions and b) dendrogram of agglomerative hierarchical clustering

Other methods implemented in b11 are useful for unsupervised data classification and cluster analysis [29]. These are the agglomerative hierarchical clustering (AHC), the similarity-based clustering method (SCM) and k-means algorithm. The AHC represent a bottom-up strategy of cluster analysis. The individual samples at first are viewed as separate clusters. The clustering algorithm computes distances between pairs of clusters in feature space. The distance between the two clusters characterizes their dissimilarity. Then, the clusters of the lowest dissimilarity are joined together. The process is repeated until the single cluster of samples forms.

The development of AHC may be visualized with a dendrogram (Fig. 3 b), which is a hierarchical tree. The tree leaves represent individual samples, branches represent links between samples or clusters, and a level at which branches join represent dissimilarity between the joined clusters. The user may 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 a density of samples within the feature space. The number of the function maxima 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 ~~turns~~ determine their membership to the corresponding cluster. The user can control the result of clustering by adjusting the parameter of the similarity function, which is responsible for the function's smoothness and the number of maxima.

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 verify the result of clustering with the k-means algorithm, the user may examine silhouette plots or a silhouette value. There are as many plots as clusters. Plots that resemble a rectangle indicate accurate clustering.

8. Feature maps and image segmentation

As already mentioned MaZda computes also feature distributions within the image (feature maps). The map is a grey-scale image, in which a gray level represents a particular textural feature value. The feature at a given image location is computed within a rectangular region (a mask) centered at this location. During the analysis process, 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. User may 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 to partition an 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 segmentation region, others fall into the other segmentation region. Unfortunately, if the goal is to segment texture, the image gray level thresholding alone usually fails. However, the thresholding may still be effective if preceded by a feature map computation. If the feature is found that discriminates two different textures, and then the feature map is computed on 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, the thresholding of the feature map would separate the two textures visible in the input image.A visual inspection of maps produced by MaZda may lead to conclusions on which feature maps should be used for texture segmentation.

To study a feasibility of image texture segmentation based on multiple feature maps, the unsupervised method of k-means clustering was implemented in b11 module. The MaZda user can load a number of arbitrary selected feature maps, then to enter a 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.

9. Applications

Patterns or texture areas appear in almost every visual image and thus images can be investigated with textural analysis tools, such as MaZda. The MaZda software was already utilized in many domains including MRI measurement protocol optimization, various medical studies, food quality studies and others.

Within COST B11 and B21 projects several studies on MRI scanning are carried out. To assure a quality and provide means for MRI scanner calibration, test objects [19] (phantoms), which imitate characteristics of living tissues are used. Such phantoms are visualized with different MRI scanners to produce test images. The images serve for quality control of scanners, for testing and standardization of protocols. The phantoms' images obtained in various medical centers through several years were evaluated and compared with the MaZda program. These studies conclude on phantoms usefulness for scanner quality testing and on the phantoms invariability in time as to be used for scanner calibration.

Texture analysis was also performed to identify and discriminate biomedical image areas, which have different textural characteristics. In medical applications textural image analysis has been used for the characterization and discrimination of image areas that represent healthy and pathological tissues. The researches involved: detection of amygdale activation in rat brains [22], to detect and quantify hipocampal sclerosis, to distinguish between brain tumors [1], discrimination of healthy and cirrhotic livers, textural analysis of trabecular bone images targeted at osteoporosis detection [13, 23], monitoring of atrophy and regeneration of muscles [15], monitoring of teeth implants [12], analysis of myocardium tissue in ultrasound images [17], assessment of cellular necrosis in epithelial cell [18] and evaluation of anti-vascular therapy of mammary carcinomas in mice [2].

The textural analysis is useful not only in medicine. The other fruitful application of such analysis is in agriculture and food processing industry. The MaZda tools turned out to be useful in discrimination between potato varieties, cooked and raw potatoes, analysis of the influence of apple ripening process on storage [20], and assessment of soft cheeses quality [3]. More examples related to MaZda applications can be also found in [19].

The MaZda package is an efficient and reliable set of tools for analysis of image textures. Its efficiency was also confirmed by the COST projects participants and other researchers, who applied this software for many different texture analysis tasks. Compared to other texture analysis software, like Keyres [8] or LS2W [9], it provides complete analysis path of textures images, including feature estimation, statistical analysis of feature vectors, classification and image segmentation. Additional information on MaZda package and its executable code can be found on the web page [7] of the Institute of Electronics, Technical University of Łódź.

Acknowledgments

The development of MaZda package was in part done within the COST B11 and B21 European projects.

References

[1] L. Bonilha, E. Kobayashi, G. Castellano, G. Coelho, E. Tinois, F. Cendes, L. M. Li, “Texture Analysis of Hippocampal Sclerosis”, *Epilepsia*, 44, 12, 2003, pp. 1546–1550.

[2] 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, pp. 3399-405.

[3] G. Collewet, M. Strzelecki, F. Mariette, “Influence of MRI acquisition protocols and image intensity normalization methods on texture classification”, *Magnetic Resonance Imaging*, 22, 2004, pp. 81-91.

[4] R. Duda, P. Hart, “Pattern Classification and Scene Analysis”, Wiley, 1973.

[5] K. Fukunaga, “Introduction to Statistical Pattern Recognition”, Academic Press, New York, 1991.

[6] R. Hecht-Nielsen, *„Neurocomputing“*, Addison-Wesley, 1989.

[7] http://www.eletel.p.lodz.pl/cost (visited: September 2007)

[8] http://www.keyres-technologies.com (visited: September 2007)

[9] http://www.maths.bris.ac.uk/~wavethresh/LS2W (visited: September 2007)

[10] A. Jain, R. Dubes, *“Algorithms for Clustering Data”*, Prentice Hall, 1998.

[11] D. Jirák, M. Dezortová, P. Taimr, M. Hájek, “Texture analysis of human liver”, *Journal of Magnetic Resonance Imaging*, 15, 1, 2002, pp. 68–74.

[12] 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, 181, 2007, pp. 40-43 (in Polish).

[13] 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, pp. 814-819.

[14] 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, pp. 719-727.

[15] 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, pp 167-171.

[16] J. Mao, A. Jain, “Artificial Neural Networks for Feature Extraction and Multivariate Data Projection” *IEEE Trans. Neural Networks,* 6, 1995, pp. 296-316.

[17] 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, pp. 435 – 440.

[18] 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.
[19] *“Texture Analysis for Magnetic Resonance Imaging”*, (eds. M. Hajek, M. Dezortova, A. Materka, R. Lerski), Med4publishing, Prague, 2006.
[20] 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*, 2004, pp. 91-100.
[21] M. Yang, K. Wu, “A Similarity-Based Robust Clustering Method”, *IEEE Trans. on Pattern Analysis and Machine Intelligence*, 24, 4, 2004, pp. 434-448.
[22] 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, January 2007, pp. 144-146.
[23] 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, Vol. 22, Issue 2, February 2004, Pages 237-243
[24] P. Szczypiński, M. Kociołek, A. Materka, M. Strzelecki, *Computer Program for Image Texture Analysis in PhD Students Laboratory*, International Conference on Signals and Electronic Systems, Łódź-Poland 2001, pp.255-262
[25] M. Kociołek, A. Materka, M. Strzelecki, P. Szczypiński, *Descrete Wavelet Transform-Derived Features for Digital Image Texture Analysis*, International Conference on Signals and Electronic Systems, Łódź-Poland 2001, pp.99-104
[26] P.M. Szczypinski, *Center Point Model of Deformable Surface* Computer Vision and Graphics, International Conference, ICCVG 2004, Warsaw, Poland, September 2004, pp.343-348
[27] A. Materka, M. Strzelecki, “Texture Analysis Methods – A Review,” Technical University of Lodz, Institute of Electronics, COST B11 report, Brussels 1998, online: http://www.eletel.p.lodz.pl/cost/pdf_1.pdf
[28] V. Kindratenko, "Development and Application of Image Analysis Techniques for Identification and Classification of Microscopic Particles", Ph.D. Thesis, University of Antwerp, Belgium, 1997, http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/KINDRATENKO1/part2.pdf
[29] A. Klepaczko, “Zastowanie algorytmów analizy skupień do selekcji cech dla zadań klasyfikacji wektorów danych”, Ph.D. Thesis, University of Lodz, Poland, 2006
[30] R. Haralick, “Statistical and Structural Approaches to Texture”, Proc. IEEE, 67, 5, 786-804, 1979