Medical Multimedia and Multimodality Databases

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1. Introduction

Recent advances in computer technology and software have resulted in a shift from paper-based medical record to electronic medical record systems. Although electronic databases have been used in medical research for analysis of data for years, computerized information systems rarely have been used for collection of data during actual patient-physician interactions. The essential parts on this data are the medical images. Management of medical images has become a major issue for the development of healthcare in the last decades. Several medical devices produce medical images, such as: X-ray, X-ray computed tomography (CT), magnetic resonance (MR), magnetic resonance spectroscopy (MRS), single photon emission computer tomography (SPECT), positron emission tomography (PET), ultrasound, electrical source (ESI), electrical impedance tomography (EIT), magnetic source (MS) and magnetic optical images. Medical systems suppose to have tools to analyze multidimensional and multimodal medical images in order to improve diagnosis and therapy, especially when therapy is guided by medical images (video-surgery, interventional radiology, radiotherapy, etc.).

The main sources in the medical multimedia systems are images with associated text and possibly speech. Special algorithms are applied to “understand” the data content and retrieve the required information. The system's queries are based on a description of the subject or by examples. The databases are structured in a modular fashion, in such a way it allows people with different knowledge to access the information in a format which can be easily understood. Medical systems contain techniques for shape-based object recognition, algorithms for speech recognition, and a suitable user interface to access the multimedia information. Such systems are composed of several modules, devoted to the semantic processing of images and speech. The main functions for such systems are: extraction of quantitative parameters useful for diagnosis (shape, texture, motion); spatial registration of images acquired at different times; fusion of multimodal images; analysis of deformable motion; construction and use of digital anatomical atlases; functional brain analysis; building virtual patients and simulation of surgery; spatial localization of patients and surgical tools.

Multimodal images of the same person or of different persons generally differ by local geometric differences, and to map such images into one coordinate system elastic transformations are required. Fused image data can improve medical diagnosis, surgery planning and simulation as well as intraoperative navigation. It enables to integrate different images into one representation such that the complementary information can be accessed more easily and accurately.

In this chapter we discuss mainly the problems witch arise working with MR image. As an illustration of medical image processing tools we discuss MR brain segmentation problems. Functional analysis of different medical systems is made. We emphasize on the fact that working with medical images is different from working with other kind of images. As an illustration two systems are presented. The first system is MEDIMAGE, which is a multimedia database for Alzheimer’s disease patients. It contains MR images, text and voice data and it is used to find some correlations of brain atrophy in Alzheimer’s patients with different demographic factors. The second system is Epilepsy system, which includes image data from MRI and SPECT, scans and EEG analysis results and it is used for patients with epilepsy.

2. Review of Medical Multimodality and Multimedia Systems

Medical multimedia and multimodality databases supports multimedia and multimodality data types, handle very large number of multimedia objects, high-performance, high-capacity, cost-effective storage and information retrieval capabilities. It includes features for acquisition, review, interpretation, management and communication of multimodality images, expandable and open system architecture, database management, friendly user-interface. They are continuation of the development of image database systems [19, 21, 34].

In the medical multimodality and multimedia systems the main effort is put on advances in technology that have increased the capability to produce images, to manipulate them and improve the medical diagnosis. There are mainly two general methods for image comparison: intensity-based (colour and texture) and geometry-based (shape). A recently held user survey shows that users are often more interested in retrieval by object shape than by colour and texture. However, retrieval by shape is still considered one of the most difficult aspects of content-based search. Indeed, systems such as IBM's QBIC, Query By Image Content (http://wwwqbic.almaden.ibm.com), perhaps one of the most advanced systems to date, is successful in retrieving by colour and texture, but not too much by shape. A similar behaviour shows Alta Vista photo finder (http://image.altavista.com/cgi-bin/avncgi). The departing point in the medical multimodality and multimedia systems is the shape similarity measure based on the correspondence of visual parts. While much work has already been done in the direction of matching point sets, two curves, or two regions, little attention so far has been paid to developing methods for matching a collection of curves and regions against another collection, which is essential for the medical images.

There are several specific requirements for medical images such as: (a) What kind of images to be acquired? (b) How the interested characteristics to be obtained? As an illustration how such problems are solved we will give our understanding of the problems dealing with the segmentation and volume calculation of grey matter (GM), white matter (WM) and Cerebrospinal Fluid (CSF) in the whole brain and regions of interest using MR images.

In this chapter we will limit our analysis on only two important issues: (a) Content-based medical image retrieval techniques, and (b) Information extraction from the medical images and more specifically brain image segmentation methods. We will also present some valuable systems in these areas.

2.1 Content-based medical image retrieval techniques

The specific aim in this field is to develop a query languages and indexing methods for retrieval, based on the contents of the multimedia objects such as images. The traditional text-based image retrieval approaches have the following specifications:

- Using text-based query languages such as SQL, and retrieving partially matched results with similarity ranking;
- Handling abstract concepts and high-level objects;
- Having difficulties to describe visual features like color, texture, and irregular shapes;
- Limiting the scope of the search to a predetermined domain provided by the system’s author;

- Indexing due to the limited speed of entering the description text manually.

Recently developed content-based approaches have the following features, which are also applied for medical images:

- Using color, texture, shape, and an extendable set of descriptors such as Fourier descriptor and moment invariant. Therefore, they are capable to query based on visual characteristics of the data e.g., irregular shapes and texture features;
- Indexing procedure is relatively fast compared to the text-based method;
- Queries and retrievals are directly based on the visual objective properties of the data, so that they are reproducible procedures.

The most of the existing content-based image retrieval methods are directly based on the visual features of the images like color and texture. These methods use a similarity measure after feature extraction for classification indexing.

2.2 Brain image segmentation techniques

A large number of researches have been done in image segmentation particularly in medical image segmentation. One possible way to categorize the image segmentation methods is on the properties being used to perform the segmentation. The image properties may divide into three major categories: (a) Intensity-based segmentation; (b) Texture-based segmentation; (c) Model-based methods. However other classifications can be found in [13] that provides an excellent review and bibliography for the MRI image segmentation. We will introduce examples for each category in the following subsections.

2.2.1 Intensity-based segmentation methods

In most techniques for segmentation the user identifies the anatomy of interest by sampling points, drawing region of interest or the segmentation is done automatically. Depending on the purpose for which the images are processed different techniques for segmentation are useful. These segmentation methods can be divided into two main classes: (a) unifeature segmentation and (b) bifeature segmentation.

In unifeature segmentation only one image from the series is used for the segmentation process. It can be applied when no shading artefacts are presented in the image. The simplest case is the grey level thresholding. It is usually applied in CT data to model bones, because there is excellent contrast between the bone and the soft tissue in the CT images. However this technique does not work well in MR image segmentation where different tissue intensity ranges overlap. More powerful threshold is the connectivity utilization [14]. Surface voxels can be connected across faces, edges and corners. The connection between threshold voxels across faces can be used to extract region of interest. Bridges between objects can occur which makes the connectivity method difficult to apply. Bridges can be opened by filtering using the erosion operation from the mathematical morphology.

In the bifeature segmentation two echo images are used (usually the first is spin density and the second is T2-Weithed image). A scatter plot is constructed by plotting the points from each of the images against each other points from each tissue category to form a cluster. The scatter plot is partitioned into areas of each tissue category to construct a feature map used for the entire image segmentation. A simple method for constructing the feature map is labelling areas with the same tissue category as the nearest training point of the scatter plot. Probability methods fit each training cluster to a distribution function and construct a feature map by calculating the most probable tissue at each point of the two intensities.

Bengtsson [5] introduces MUSE, interactive software for extending the thresholding concept to multivariate images, i.e. images with more than one spectral band. Similarly [1] uses a 3D spectrum of the tissue voxels for automatic segmentation of GM, WM, and CSF. It uses the segmentation results for volume calculations. Also [35] presents a multispectral analysis of MRI as a tool to recognize common normal tissue types within the brain. Some researchers use clustering methods on the image intensities to perform unsupervised segmentation. For instance Vinitski [38] uses a k-Nearest neighborhood algorithm for brain MRI segmentation. Gesu [17] propose several automatic clustering methods including hierarchical ISODATA (HISO) to segment the brain MRI slices. Vaidyanathan [37] compares a supervised k-nearest neighbor and a semi-supervised fuzzy c-means method with two reference methods, seed growing and manual segmentation. Hall [22] compares the results of a fuzzy c-means unsupervised clustering algorithm with a supervised dynamic multilayered perception trained using the cascade correlation-learning algorithm. Supervised and unsupervised segmentation techniques provide broadly similar results in this research article. Bensaid [6] investigates the problems associate with the clustering methods for segmentation as a classification problem. Since the imaging procedure is affected by noise, statistical methods are widely used to deal with the noise effects and to improve the segmentation results. Smith [29] proposes a Bayesian method that assumes there is an unobserved label for each pixel. The label generates the intensity value of each pixel. In [10] a Bayesian approach for volumetric MRI segmentation is proposed with connectivity and smoothness constraints imposed. Wells [39] describes a method called adaptive segmentation that uses knowledge of tissue intensity properties and intensity inhomogeneities to correct and segment MR images. This method uses the expectation-maximization algorithm to get more accurate segmentation and better visualization.

2.2.2 Texture-based segmentation methods

The research done by Soltanian-Zadeh et al. [30] indicates that texture information may help to distinguish between different brain tumors and normal and abnormal tissues. Since they have used texture features along with intensity information it is not clear how well only texture features can be used for segmentation. Using texture information on MRI, Barra [4] calculate features to detect and characterize Alzheimer disease. This work characterizes the Alzheimer disease based on the whole brain dataset. The author uses the intensity information to perform brain segmentation. The author employs a fuzzy approach to model the MRI uncertainty and imprecision, and wavelet representations to incorporate the spatial and textural information. The author segments the brain to WM, GM, and CSF providing a fast, unsupervised and totally independent of any statistical assumption. Hofmann [23] presents an optimization framework for unsupervised texture segmentation using Gabor filters. Teuner [36] and Dunn [16] use multichannel Gabor decomposition for unsupervised segmentation and boundary detection. Chen [11] describes an automatic unsupervised texture segmentation schema, using hidden Markov models. Choi [12] employs a multivariate linear discriminant algorithm. He computes the classical Haralick and Pressman features within a 3×3×3 neighborhood. Then he adds the color information to perform the final segmentation. There is doubt for us if the texture features significantly represent the brain tissues since the methods mentioned here use texture features along with the intensity information.

2.2.3 *Model-based segmentation methods*

Atlas warping and knowledge-based approaches have pre-defined assumptions about the brain structures. Atlas-based methods have certain elements of a 3D brain template to fit the corresponding elements of the patient's brain. A warping function usually governs the dynamics under which the template from the brain atlas is fitting on the patients' brain. The more landmarks and the higher degree of freedom the warping function supports, the better matching occurs between two datasets, i.e. brain atlas and patient's brain. Knowledge-based methods have also pre-assumptions regarding the relative spatial relationships between brain structures. They usually utilize search methods restricted by anatomical knowledge and materialized in a rule-based system to find and segment the brain structures.

Brown [9] introduces a knowledge-based approach for chest CT image segmentation. Lundervold [26] aims to segment brain parenchyma and CSF in MR images. The algorithm simultaneously incorporates information about anatomical boundaries (shape) and tissue signature (gray scale) using a priori knowledge. Ashton [2] proposes a technique making use of combination of gray scale and edge-detection algorithms and some a priori knowledge to provide an unsupervised segmentation for hippocampus structure. Yan [40] presents a method that models each tissue type by Markov random field in a 3D lattice. The proposed method is an adaptive K-means clustering algorithm for 3D and multi-valued images. Atkins [3] proposed a robust fully automatic method for brain segmentation from skull and eyes on human brain MRI. The method uses anisotropic filters and snakes (deformable 2D) contouring techniques and a priori knowledge. He uses a priori knowledge to remove the eyes. Siadat [28], Soltanian-Zadeh [31], and Ghanei [18] propose a knowledge-based 3D deformable model for hippocampus segmentation.

2.2.4 *Problems in MR image segmentation and measurements in MR images*

We classify some of the problems derived with segmentation and measurements in MR images into three categories: (a) image acquisition problems; (b) segmentation problems; (c) measurements problems.

2.2.4.1 MR image acquisition problems

- <u>What kind of image to be used for the segmentation?</u> Usually spin density and T2-Weithed images are used. Except for T2-Wethed, T1-Weithed images can also be used. In our opinion the implementation of the three series will give better results. The problem is in the acquiring of such series of data and the constructing of a three-feature map.

- <u>Acquiring MR images with low signal to noise ratio.</u> The signal to noise ratio is one of the most important quality criteria in an image quality. For MR images it depends on the number of protons per pixel. The ratio improves in thicker slices; it degrades in images with larger matrix and it is linearly proportional to the field strength and is a factor of square root of the number of averaging. We establish that images obtained with a field strength of 1.5 Tesla, number of averaging equal to 1 and image matrix 256 x 256 are good for segmentation. Using different protocols we found that the signal to noise ratios vary between 83.05 (± 3.01) to 86.79 (±0.81) in a phantom MR images.

- Choosing the thickness of the image slices**.** The thinnest possible slices should be obtained, because this reduces the partial volume averaging artefacts. According to Kohn [25] there is no statistically significant difference between volume calculation results obtained from 3 mm tick slices and those obtained from 5 mm slices. We found that axial spin density and T2-Weithed images as 5 mm slices with 2.5 mm gap are good for segmentation and coronal images as 1.3 mm slices are good for measurement of different brain structures.

- Choosing the image acquiring parameters. The MR images has to be obtained with good contrast and quality. We found that sagittal images with TE = 19 ms, TR = 650 ms, axial images with TE1= 30 ms, TE2 = 80 ms, TR = 2400 ms and coronal images with TE = 5 ms, TR = 23 ms and flip angle = 35 degrees are good for segmentation and structure measurements.

- Making symmetrical images. This is important for volume calculation, if we want to compare the volume of some structure in the left and right part of the brain. To obtain this goal a series of sagittal images has to be obtained first and used for orientation.

2.2.4.2 MR image segmentation problems

- Choosing between sagittal, axial and coronal images for a particular calculation. According to Kohn [25] there is statistically no difference what kind of images are selected. Ideally, the plane containing the greatest structural complexity should be parallel to imaging plane. However the coronal plane is preferable because there is less section-to-section contour variation compared with such variation in the sagittal and axial planes. We found that sagittal images are good for orientation, axial making parallel to AC-PC line for volume calculation of the WM, GM and CSF, and coronal images making perpendicular to hippocampal formation for hippocampal volume calculation.

- How to compare the segmentation made by different observers? Some structures overlap and anatomic knowledge between the observers can be different. So our solution is that the observers has to use the standard stereotactic atlas [33] when they select points or draw lines, or select region of interests. The problem here is that the thickness of the slices and the gap between them varies from slice to slice in this atlas. In our studies we obtain 0.97 as interoperator correlation and 0.98 as intraoperator correlation.

2.2.4.3 MR images measurement problems

- How many images from the series to be used to calculate the volume of the different structures of the brain? We have found that the very first and last images are usually not good enough for the purpose of the segmentation process. We use as a first slice the slice in which the cerebellar hemisphere appears and the last slice, where the top of the brain can be seen for image segmentation.

- How to remove from the images structures that are not of interest? Such structures are usually eyes, mussels, fatty tissue of scalp in brain MR images. Because such structures are usually segmented as CSF we found that they have to be removed from the images if we used them for segmentation. Possible ways are manually or using morphological filters.

- How to calculate the volume of the boundary voxels? Algorithms which approximated the boundary voxels has to be used. They taken into account the surface shape and interpreting the tissue regions as polygons.

- How to calculate the normalized tissue volume**.** The user needs such data if he wants to compare the amount of the brain tissue volume of different patients. Different people have different volume of the brain. One way to normalize the volume of brain tissues is by using the whole grain volume. Another way which we chose is to normalize the volume by using AC-PC distance, given in the standard stereotactic atlas [33].

2.3 Medical systems working with multimedia and multimodality information

A list of valuable multimedia and multimodality medical systems includes:

- QUICKSEE - a system for endoscopic exploration inside 3D radiological images and text [http://cobb.ece.psu.edu/krishnan/krish_home.html];
- The database of the anatomic MRI brain scans of children across a wide range of ages to serve as a resource for the pediatric neuroimaging research community [27];
- BrighamRAD teaching case database department of radiology, Brigham and Women's Hospital Harvard Medical School [8];
- BrainWeb Simulated Brain Database site of a normal brain and a brain affected by multiple sclerosis [15]. [http://golgi.harvard.edu/biopages/medicine.html];
- MedPix™ [http://rad.usuhs.mil/synapse/radpix.html] is a fully web-enabled and cross-platform database, integrating images and textual information. The primary "target audience" includes physicians, medical students, graduate nursing students and other post-graduate trainees. The material is organized by disease category, disease location (organ system), captions, and by patient profiles. MedPix™ can be searched through multiple internal image and text search engines;
- A Medical Image Database System for Tomographic Images is described in [http://www.ics.forth.gr/ICS/acti/cmi_hta/publications/papers/1988-1994/car89/car89.html]. The attention has been focused on techniques for the automated description of anatomical crossections in terms of geometrical features which facilitate matching operations and can be used to access tomographic images by content. The organization of the image database and possible strategies for image retrieval by content are available;
- MediMedia [http://www.infowin.org/ACTS/NEWS/CONTENT_UK/981101uk.htm] provides an extensive database of medical case histories and surgical procedures. An example of the application of the MediMedia database is in pre-operative planning for the execution of medical interventions, such as hip surgery. X-ray images and CT scans taken prior to the operation are processed by the system to make 3D computerized models of the patient's bones.

3. The MEDIMAGE System

We determined topographic selectivity and diagnostic utility of brain atrophy in probable Alzheimer's disease (AD) and correlations with demographic factors such as age, sex, and education. A medical multimedia database management system MEDIMAGE was developed for supporting this work. Its architecture is based on the image database models [20], [32]. The system design is motivated by the major need to manage and access multimedia information on the analysis of the brain data. The database links MR images to patient data in a way that permits the use to view and query medical information using alphanumeric, and feature-based predicates. The visualization permits the user to view or annotate the query results in various ways. These results support the wide variety of data types and presentation methods required by neuroradiologists. The database gives us the possibility for data mining and defining interesting findings.

The MEDIMAGE system architecture is presented in the Figure 1.

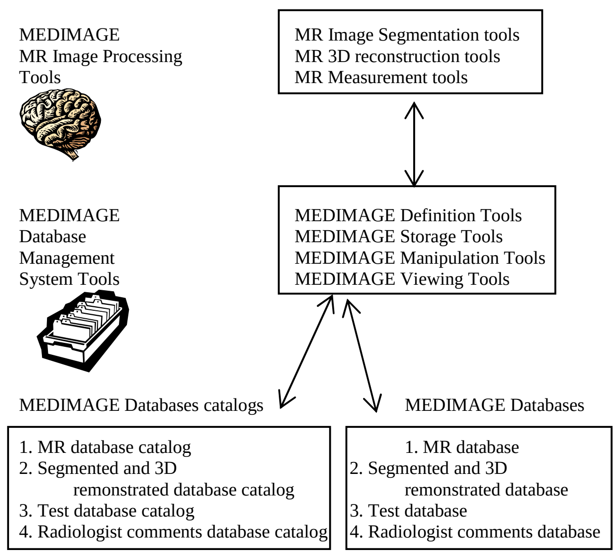


Figure 1. The MEDIMAGE system architecture

3.1 The MEDIMAGE system databases

In the MEDIMAGE system there are four databases:

a) MEDIMAGE MR Database. For brain volume calculation we store a two-spin-echo sequence covering the whole brain. 58 T2-Weithed 3 mm slices are obtained with half-Fourier sampling, 192 phase-encoding steps, TR/TE of 3000/30, 80 ms, and a field-of-view of 20 cm. The slices are contiguous and interleaved. We collect and store also 124 T1-Weighted images using TR/TE of 35/5 msec, flip angle of 35 degrees. Finally we collect patients and scanner information such as: acquisition date, image identification number and name, image modality device parameters, image magnification, etc.

b) MEDIMAGE Segmented and 3D reconstructed database. This is the collection of process magnetic resonance images – segmented and 3D rendered.

c) MEDIMAGE Test database. The test date includes patient's results from the standard tests for Alzheimer's disease and related disorders.

d) MEDIMAGE Radiologist comments database. This data are in two types: text and voice. They contain the radiologist findings.

3.2 The MEDIMAGE MR image processing tools

In the MEDIMAGE system there are three main tools for image processing.

a) **MEDIMAGE MR Image Segmentation tools.** These tools include bifeature segmentation tool and ventrical and sulcal CSF volume calculation tool. The CSF denotes the fluid inside the brain.

   - **Bifeature segmentation tool**. Segmentation of the MR images into GM, WM and CSF is performing in the following way: thirty points per compartment (15 per hemisphere) are sampled simultaneously from the proton density and T2-Weigted images. The sample index slice is the most inferior slice above the level of the orbits where the anterior horns of the lateral ventricles could be seen. Using a nonparametric statistic algorithm (k-nearest neighbors supervised classification) the sample points are used to derive a "classificator" that determined the most probable tissue type for each voxel.
   - **Ventrical and sulcal CSF volume calculation tool.** A train observer places a box encompassing the ventricles to define the ventrical CSF. Subtraction the ventical from the total CSF provided a separate estimate of the sulcal CSF.

b) **MEDIMAGE MR 3D reconstruction tools.** These tools include total brain capacity measurement and region of interest definition tools.

- **Total brain capacity measurement tool.** A 3D surface rendering technique is used to obtain accurate lobal demarcation. The T2-weighted images are first "edited" using intensity thresholds and tracing limit lines on each slice to remove nonbrain structures. The whole brain volume, which included brain stamp and cerebellum, is then calculated from the edit brain as an index of the total intracranial capacity and is used in the standardization procedures to correct for brain size. A 3D reconstruction is computed.
- **Region of interest definition tool**. Using anatomical landmarks and a priori geometric rules accepted by neuroanatomic convention, the frontal, parietal, temporal, and occipital lob are demarcated manner. The vovels of the lobar region of interest is used to mask the segmented images, enabling quantification of different tissue compartments for each lobe.

c) **MEDIMAGE MR Measurement tools.** These tools include Hippocampal volume determination tool.

- **Hippocampal volume determination tool.** Sagical images are used to define the anterior and posterior and end points of the structure. Then they are reformatted into coronal slices perpendicular to the longitudinal axis of the hippocampal formation. Then the hippocampal perimeter is traced for each hemisphere. The demarcated area is multiplied by slice thickness to obtain the hippocampal volume in the slice.

3.3 The MEDIMAGE database management tools

In the MEDIMAGE database management system there are definition, storage, manipulation and viewing tools.

a) **MEDIMAGE Definition Tools.** Those tools are used for defining the structure of the four databases. All of them are using relational model.

b) **MEDIMAGE Storage Tools.** These are tools allowing entering, deletion and updating of the data in the system.

c) **MEDIMAGE Manipulation Tools.** Those tools allow: image retrieval based on alphanumeric and feature-based predicates and numerical, text, voice and statistic data retrieval.

- Image retrieval based on similarity retrieval. Let a query be converted in an image description $Q(q_1, q_2, \ldots, q_n)$ and an image in the image database has the description $I(x_1, x_2, \ldots, x_n)$. Then the retrieval value (RV) between Q and I is defined as: $RV_Q(I) = \Sigma_{i = 1, \ldots, n} (w_i * sim(q_i, x_i))$, where w_i ($i = 1,2, \ldots, n$) is the weight specifying the importance of the i^{th} parameter in the image description and $sim(q_i, x_i)$ is the similarity between the i^{th} parameter of the query image and database image and is calculated in different way according to the q_i, x_i values. There are alphanumeric and feature-based predicates.

- **Numerical, text, voice and statistic data retrieval.** A lot statistical function are available in the system allowing to make data mining using the obtain measurements and correlated them with different demographic factors.

d) **MEDIMAGE Viewing Tools.** Those tools allow viewing images and text, numerical and voice data from the four databases supported by the system.

3.4 Results obtained with the MEDIMAGE system

The results of some of the image processing tools are given in Figures 2-7. Result from the statistical analysis applied to MR images in 32 patients with probable AD and 20 age- and sex-matched normal control subjects find the following findings. Group differences emerged in grey and white matter compartments particularly in parietal and temporal lobes. Logistic regression demonstrated that larger parietal and temporal ventricular CSF compartments and smaller temporal grey matter predicted AD group membership with an area under the receiver operating characteristic curve of 0.92. On multiple regression analysis using age, sex, education, duration, and severity of cognitive decline to predict regional atrophy in the AD subjects, sex consistently entered the model for the frontal, temporal, and parietal ventricular compartments. In the parietal region, for example, sex accounted for 27% of the variance in the parietal CSF compartment and years of education accounted for an additional 15%, with women showing less ventricular enlargement and individuals with more years of education showing more ventricular enlargement in this region. Topographic selectivity of atrophic changes can be detected using quantitative volumetry and can differentiate AD from normal aging. Quantification of tissue volumes in vulnerable regions offers the potential for monitoring longitudinal change in response to treatment.

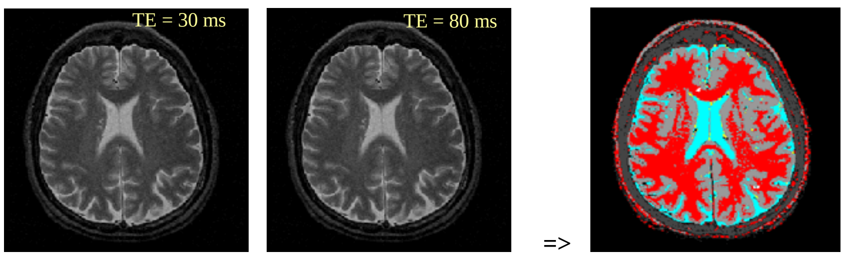


Figure 2. Bifeature segmentation

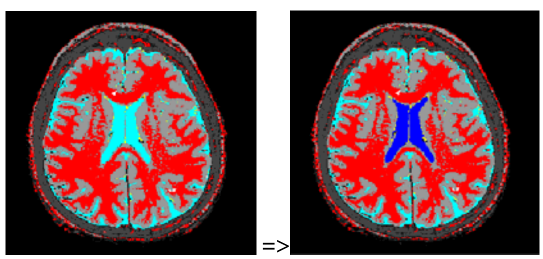


Figure 3. Ventricular and Sulcal CSF Separation

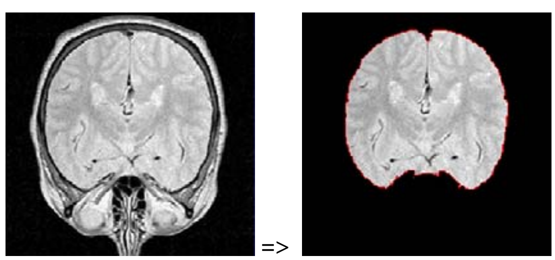


Figure 4. Brain Editing

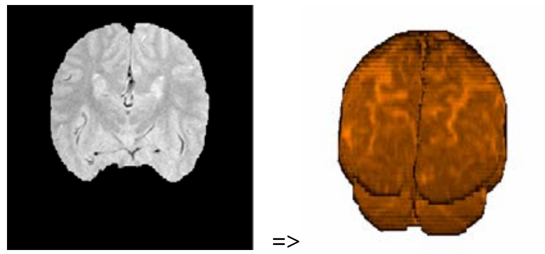


Figure 5. 3D Brain Reconstruction

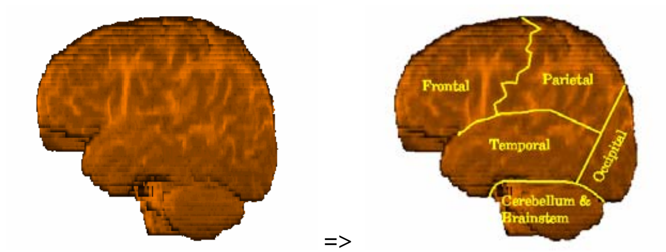


Figure 6. Region Definition

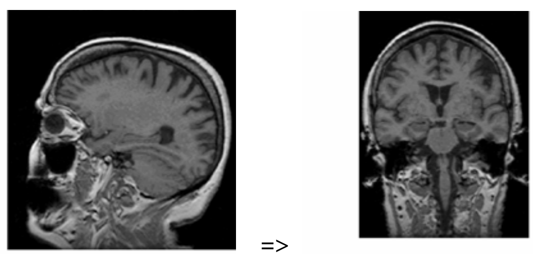


Figure 7. Hippocampal Volume Calculation

3.5 The MEDIMAGE system summary

The MEDIMAGE system was developed in the Sunnybrook health science centre, Toronto, Canada, on SUN Microsystems. It uses GE scanner software and ANALYSE and SCILIMAGE packages. The medical findings are described in details in [24]. The main advantages of the proposed MEDIMAGE system are: (a) generality. The system could easily modify for other medical image collection. The system was use also for corpus colosam calculations [7]; (b) practical applicability. The results obtained with the system define essential medical findings.

4. The Epilepsy System

The Epilepsy system data includes MRI and SPECT scans and EEG analysis data. A new segmentation method is utilized for information extraction and indexing. The proposed system is capable of content-based image retrieval. Finding the correlations between symptoms, treatment planning, and outcomes of the neurosurgery within a largely populated database helps neurosurgeons to determine surgery candidacies.

4.1 The Epilepsy system architecture

The system architecture is shown in Figure 8. The "Segmentation Module" generates a 3D model for the desired structure within the brain from the specified image modality. The structure model then will be stored in the database along with the parameters used to build the model via "Query Module." The "Query Module" acts like a mediator. According to the query it decides from which modality the information should be retrieved and which wrapper-parameters should be employed. Further, it activates the applications such as histogram analysis modules to determine the parameters for localization procedure. The histogram analysis module is within the "localization procedure parameter settings" and it determines the thresholds for generating the binary images. The parameters for "3D deformable model" is pretty much fixed for each desired structure. So depending on the desired structure "Query Module" retrieves the proper parameters from the database. The wrapper for visual feature extraction is a batch file that calculates the visual features within the specified structure model. The features should be calculated over a proper image modality. The decision about which structure and which image modality should be used is made by "Query Module" and according to the query issued by user. The wrapper includes registration module to align the specified image modality with the modality on which the structure model has been generated. For the EEG signal, the wrapper (a non-visual feature extractor) can be either a 1D signal processing algorithm or an expert/specialist. We decided to have the experts to do the job since it is a routine in our clinics (at Henry Ford Hospital) and it is done according to a well-defined standard. For unstructured text information, the wrapper is either a trained nurse (data analyst) or natural language analyzer software. In our case, we decided to have a trained nurse to extract the information. The output of feature extraction for unstructured non-visual data fills out our predefined tables resulting in "loose of information" and "subjectivity" of the proposed database. The structured data does not need to be analyzed by the wrapper and can be directly stored in the database via database applications. System author is either an individual surgeon/neuroscientist or a group of them and the users are they themselves or their students or patients.

The queries that will be issued are like:

- What is the correlation between the ratios of hippocampi volumes before the surgery vs. temporal lobe epilepsy as the signature of the disease? The possible retrieved information may look like Fig. 3-4.

- What is the correlation between the ratios of hippocampus resection over its volume before the surgery vs. memory quotient?

- What is the correlation between attribute_X of the entity_Y and the patient memory quotient? Where entity_Y is a brain structure such as hippocampus and attribute_X is any feature of the structure.

- What is the average of R_V (minus) L_V (L_V and R_V stand for the volumes of the left and right hippocampi, respectively)?

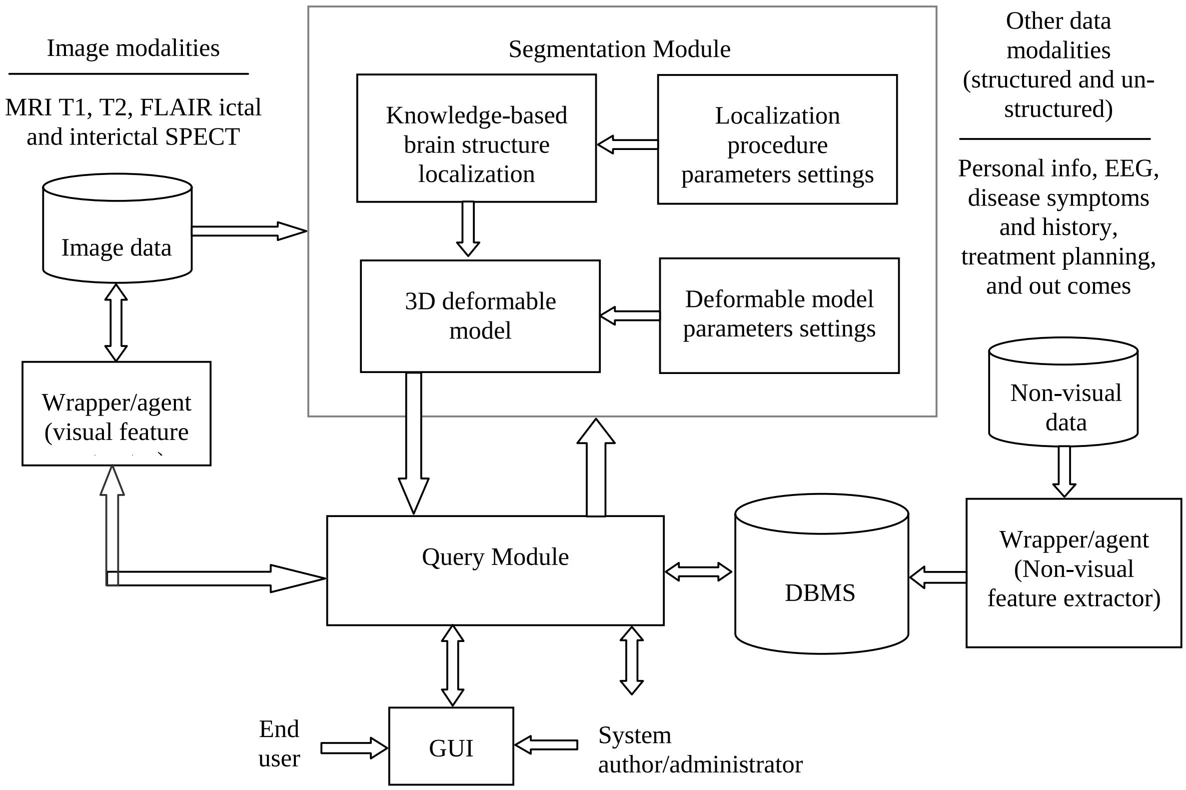


Figure 8. The Epilepsy system architecture

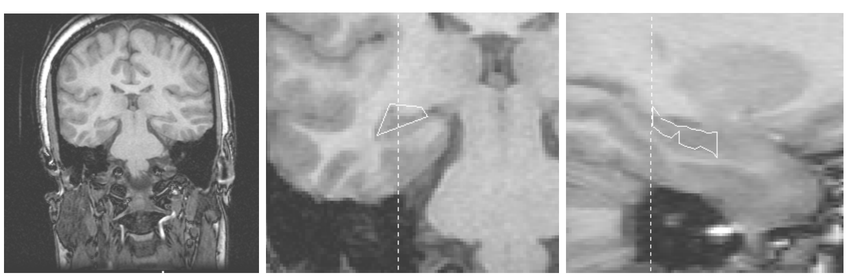
4.2 The Epilepsy system methods

Image segmentation methods consist of a new knowledge-based segmentation method and a database with an extendable schema. We use a set of 33 rules to localize the hippocampus in T1-Weighted MRI. Hippocampus is an important brain structure for epilepsy diagnosis with no/low contrast boundaries and multiple edges in some parts. A 3D deformable model evolves the initial localization of the hippocampus to fit its exact surfaces. After segmentation, different image modalities are registered onto the segmented one. The volume, surface area, and intensity mean-value and standard deviation are calculated based on the hippocampus model. Other features are the calculated over the model and added to the database as new attributes of the hippocampus. The schema proposed for the database is extendable i.e. new attributes, entities, and relationships, can be added as they become available. The content of the dataset within the segmented model such as signature vector, texture, and shape is queried resulting in the content based image retrieval capability.

4.3 Results obtaining with the Epilepsy system

We have segmented the hippocampus structure from 24 patients' T1-Weighted MRIs and calculated its attributes (volume, surface area, intensity mean-value and standard deviation) within the segmented model. The query "What is the average of R_V (minus) L_V (L_V and R_V stands for the volumes of the left and right hippocampi) for patients with left-side operation before the surgery?" resulted 275.7 pixels for 10 patients with left side operation. In Figure 9 the initial localization of the hippocampus by the knowledge-based method proposed in [28] and [31] is shown. The left column contains the coronal MRI scans; the right column the zoomed in view of a sagittal slice with a polygon drawn around the hippocampus; and in the center column - zoomed in view of the left column taken from the slices perpendicular to the dash-lines shown on the right column. In Figure 10 the final results of the hippocampus segmentation using the initial polygon shown in Figure 9, performed by 3D deformable model [18] is shown. In the left column the coronal MRI scans are given; in the right column the zoomed in view of a sagittal slice with the accurate segmentation of the hippocampus; and in the center column the zoomed in view of the left column taken from the slices perpendicular to the dash-lines shown on the right column.

Furthermore, other brain structures such as parahippocampal gyrus are also segmented and added to the database as new entities along with their attributes.



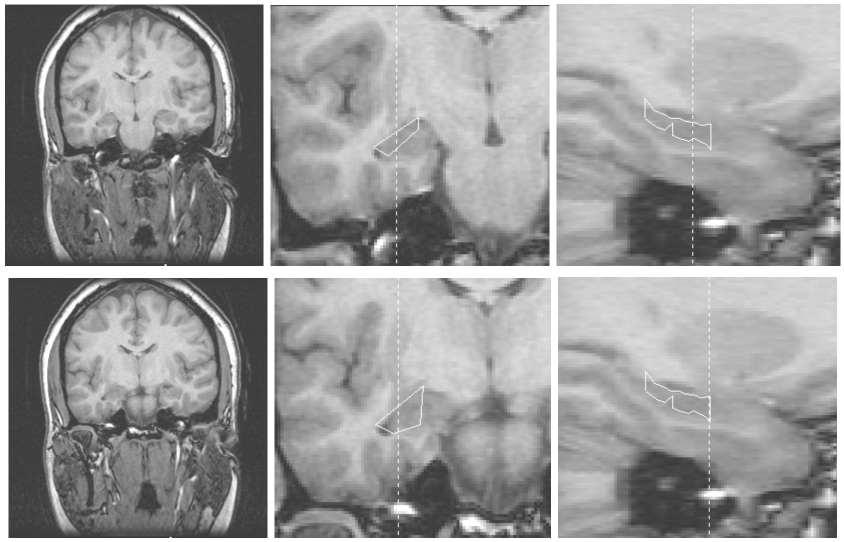


Figure 9. The initial localization of the hippocampus by the knowledge-based method

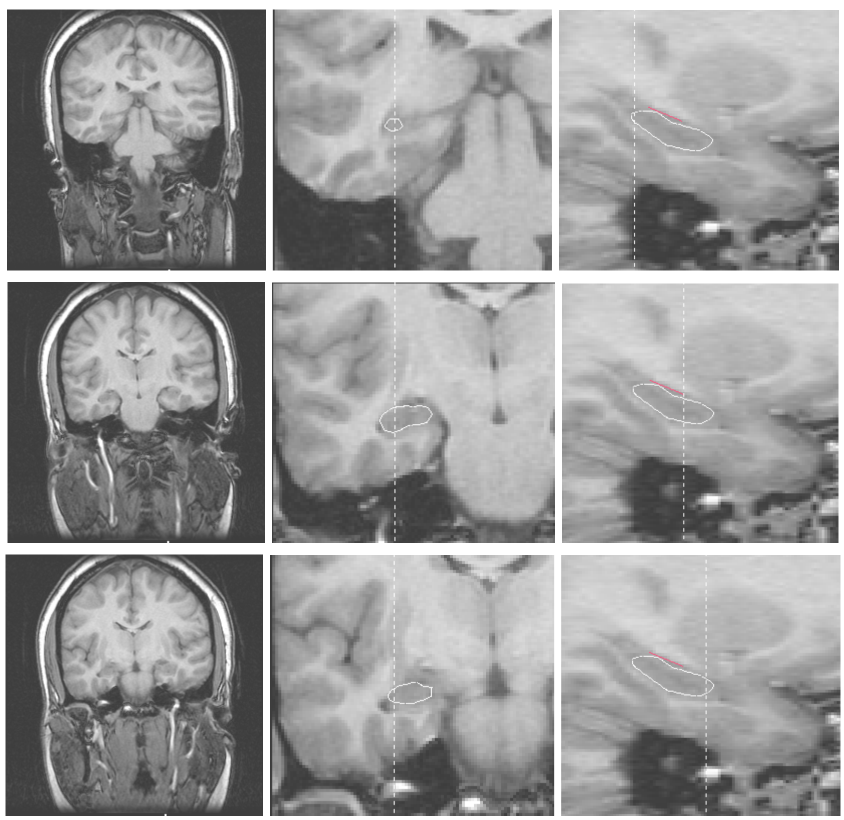


Figure 10. The final results of the hippocampus segmentation

5. *Conclusions*

The advances in medical imaging over the last two decades have a compact effect on diagnosis, treatment planning and evaluation. Despites of the available medical multimedia and multimodality systems a lot has to be done in the future using the multimedia technology. They have to cover:

- A-click-away information available for the surgeon about the previously treated patients similar to the current case especially in terms of their visual characteristics;
- Keep track and to provide conclusions about a group of patients undergone through a particular treatment plan over the past period of time;
- To evaluate the disease and results of the treatment plan, and their quantitative effects on the normal/abnormal structures/tissues of the brain based on the scanned image data sets;
- Having the previous case experiments/documents and providing easy access to the meaningful patient's information.

On the other hand, the patient's medical image data form a huge source of information. The medical data for each individual patient should be augmented with the neurological knowledge and surgery experiences in the expert's mind to perform diagnosis, treatment planning, treatment evaluation, and to discover correlations between symptoms, planning, treatments, and their outcomes. Considering the huge amount of the patient's data, it is impossible for a human being to keep track of all parts of it specially its quantitative aspects. We hope that the area of the multimedia and multimodality medical system is a very rapid growing area and we expect a lot of research in the very near future.

The main conclusion of the use of our systems is that the content-based image retrieval is not the essential part in such kind of system. Data mining algorithms play essential roles in similar systems.

6. References

[1] Alfano B., Brunetti A., Covelli E. M., Quarantelli, M., Panico, M. R., Ciarmiello, A., Salvatore, M., "Unsupervised, Automated Segmentation of the Normal Brain Using a Multispectral Relaxometric Magnetic Resonance Approach," *MRM*, vol. 37, pp. 84-93, 1997.

[2] Ashton, M., Berg, J., Parker, K. J.,Weisberg, J., Chen, C. W., Ketonen, L., "Segmentation and Feature Extraction Techniques, with Applications to MRI Head Studies," *MRM*, vol. 33, pp. 670-677, 1995.

[3] Atkins M. S., Mackiewich B. T., "Fully Automatic Segmentation of the Brain in MRI," *IEEE Trans. on Medical Imaging*, vol. 17, no. 1, February 1998.

[4] Barra V., Boire J-Y., "Tissue Segmentation on MR Images of the Brain by Possibilistic Clustering on a 3D Wavelet Representation," *J. of Magnetic Resonance Imaging*, vol. 11, pp. 267-278, 2000.

[5] Bengtsson E., Nordin B., Pederson F., "MUSE — A New Tool for Interactive Image Analysis and Segmentation based on Multivariate Statistics," *Computer Methods and Programs in Biomedicine, Elsevier Publishers*, vol. 42, pp. 181-200, 1994.

[6] Bensaid A. M., Hall L. O., Bezdek J. C., et. al., "Validity-Guided (Re)Clustering with Applications to Image Segmentation," *IEEE Trans. on Fuzzy Systems*, vol. 4, no. 2, May 96.

[7] Black SE. Moffat SD. Yu DC. Parker J. Stanchev P. Bronskill M. "Callosal atrophy correlates with temporal lobe volume and mental status in Alzheimer's disease." Canadian Journal of Neurological Sciences. 27(3):204-9, 2000 Aug.

[8] BrighamRAD Teaching Case Database Department of Radiology, Brigham and Women's Hospital Harvard Medical School - http://brighamrad.harvard.edu/education/online/tcd/tcd.html

[9] Brown M. S., McNitt-Gray M. F., Mankovich N. J., Goldin J. G., Hiller J., Wilson L. S., Aberle D. R., "Method for Segmentation Chest CT Image Data Using an Anatomical Model: Preliminary Results," *IEEE Trans. on Medical Imaging*, vol. 16, no. 6, December 1997.

[10] Chang M. M., Tekalp A. M., Sezan M. I., "Bayesian Segmentation of MR Images Using 3-D Gibbsian Priors," *SPIE vol. 1903, Image and Video Processing*, 1993.

[11] Chen J-L., Kundu A., "Unsupervised Texture Segmentation Using Multichannel Decomposition and Hidden Markov Models," *IEEE Trans. on Image Processing*, vol. 4, no. 5, May, 1995.

[12] Choi H-K, Bengtsson E., "A Direct Way of Combining Texture and Color for Image Segmentation," *SCIA97*, June 9-11, 1997.

[13] Clarke L. P., Velthuizen R. P., Camacho M. A., Heine, et al., "MRI Segmentation: Methods and Applications, Elsevier Publishers," *Magnetic Resonance Imaging*, vol. 13, no. 3, 1995.

[14] Cline H., Dumoulin C., Hart H., Lorensen W., Ludke S., "3D Reconstruction of Brain from Magnetic Resonance Images Using a Connectivity Algorithm", Magnetic Resonance Imaging, Vol. 5 (1987) 445-352.

[15] Cocosco C.A., Kollokian V., Kwan R.K.-S., Evans A.C.: "BrainWeb: Online Interface to a 3D MRI Simulated Brain Database", NeuroImage, vol.5, no.4, part 2/4, S425, 1997 - Proceedings of 3-rd International Conference on Functional Mapping of the Human Brain, Copenhagen, May 1997.

[16] Dunn D., Higgins W. E., "Optimal Gabor Filters for Texture Segmentation," *IEEE Trans. on Image Processing*, vol. 4, no. 7, July 1995.

[17] Gesu V. D., Romeo L., "An Aplication of Integrated Clustering to MRI Segmentation," *Pattern Recognition Letters*, vol. 15, pp. 731-738, 1994.

[18] Ghanei Amir, "A Knowledge-Based Deformable Surface Model for Analysis of Medical Images," PhD dissertation, The University of Michigan, 2001.

[19] Grosky W., Mehrotra R.: "Image Database Management". IEEE Computer, 22, 1989, 7-8.

[20] Grosky W., Stanchev P., "Object-Oriented Image Database Model", 16th International Conference on Computers and Their Applications (CATA-2001), March 28-30, 2001, Seattle, Washington (94-97).

[21] Gudivada V., Raghavan V., Vanapipat K.,: "A United Approach to Data Modeling and Retrieval for a Class of Image Database Applications", in Subrahmanian V., Jajodia S., Multimedia Database Systems, Springer 1996, 37-78.

[22] Hall L. O., Bensaid A. M., Clarke L. P., Velthuizen R. P., Silbiger M. S., Bezdek J. C., "A Comparison of Neural Network and Fuzzy Clustering Techniques in Segmenting Magnetic Resonance Images of the Brain," *IEEE Trans. on Neural Networks*, vol. 3, no. 5, September 1992.

[23] Hofmann T., Puzicha J., Buhmann J. M., "Unsupervised Texture Segmentation in a Deterministic Annealing Framework," *IEEE Pattern Analysis and Machine Intelligence*, vol. 20, no. 8, August 1998.

[24] Kidron D. Black SE. Stanchev P. Buck B. Szalai JP. Parker J. Szekely C. Bronskill MJ., "Quantitative MR volumetry in Alzheimer's disease. Topographic markers and the effects of sex and education", Neurology. 49(6):1504-12, 1997 Dec.

[25] Kohn M., Tanna N., Hermas G., Resnick S., Mozley D., Gur., Alavi A., Zimmerman R., Gur R., "Analysis of Brain and Cerebrospinal Fluid Volumes with MR Imaging", Radiology 178 (1991) 115-122

[26] Lundervold A., Storvik G., "Segmentation of Brain Parenchyma and Cerebrospinal Fluid in Multispectral Magnetic Resonance Images," *IEEE Trans. on Medical Imaging*, vol. 14, no. 2, June 1995.

[27] Pediatric Study Centers (PSC) for a MRI Study of Normal Brain Development - http://grants.nih.gov/grants/guide/noticefiles/not98-114.html

[28] Siadat M., Soltanian-Zadeh H., "An Intelligent Approach for Locating Hippocampus in Brain MRI," *Proceedings of the 16th IASTED International Conference*, Garmisch-Partenkirchen, Germany, Feb. 23-25, 1998.

[29] Smith K. R., Kendrick L. A., "Bayesian Computer Vision Methods for Improved Tumor Localization and Delineation," *IEEE Nuclear Science Symposium and Medical Imaging Conference*, Nov. 2-9, 1991.

[30] Soltanian-Zadeh H., Nezafat R., and Windham J.P.: ``Is There Texture Information in Standard Brain MRI?" *Proceedings of SPIE Medical Imaging 1999: Image Processing Conference*, San Diego, CA, Feb. 1999.

[31] Soltanian-Zadeh H., Siadat M. R., "Knowledge-Based Localization of Hippocampus in Human Brain MRI," *Proceedings of SPIE Medical Imaging 1999*, San Diego, CA, Feb. 20-26, 1999. SPIE MI99 poster honorable mention award winner.

[32] Stanchev, P., 'General Image Database Model,' *Visual Information and Information Systems, Proceedings of the Third Conference on Visual Information Systems*, Huijsmans, D. Smeulders A., (Eds.) Lecture Notes in Computer Science, Volume 1614 (1999), pp. 29-36.

[33] Tailarach J., Toumoux P., "Co-Planar Stereotactic Atlas of Human Brain", New York, Georg Thieme (1988)

[34] Tamura, H. Yokoya N.: "Image Database Systems: A Survey". Pattern Recognition, Vol. 17, No. 1 (1984) 29-43.

[35] Taxt T., Lundervold A., "Multispectral Analysis of the Brain Using Magnetic Resonance Imaging," *IEEE Trans. on Medical Imaging*, vol. 13, no. 3, September 1994.

[36] Teuner A., Pichler O., Hosticka B. J., "Unsupervised Texture Segmentation of Images Using Tuned Matched Gabor Filters," *IEEE Trans. On Image Processing*, vol. 4, no. 6, June 1995.

[37] Vaidyanathan M., Clarke L. P., Velthuizen R. P., Phuphanich S., et al., "Comparison of Supervised MRI Segmentation Methods for Tumor Volume Determination During Therapy," *Magnetic Resonance Imaging*, vol. 13, no. 5, pp. 719-728, 1995.

[38] Vinitski S., Gonzalez C., Burnett C., et al., "Tissue Segmentation in MRI as an Informative Indicator of Disease Activity in the Brain," *Image Analysis and Processing: 8th International Conference*, Italy, September 3-15,1995.

[39] Wells W. M., Grimson W. E. L., Kikinis R., Jolesz F. A., "Adaptive Segmentation of MRI Data," *IEEE Trans. on Medical Imaging*, vol. 15, no. 4, August 1996.

[40] Yan M. X. H., Karp J. S., "Segmentation of 3D Brain MR Using an Adaptive K-means Clustering Algorithm," *Proceedings of the 1994 Nuclear Science Symposium and Medical Imaging Conference. Part 4 (of 4)*, Norfolk, VA, USA, pp. 1529-1533, 1995.