ISSUES AND PROBLEMS IN BRAIN MAGNETIC RESONANCE IMAGING: AN OVERVIEW

Novanto Yudistira, Daut Daman
Department of Computer Graphics and Multimedia, Faculty of Computer Science and Information System, Universiti Teknologi Malaysia (UTM), 81310, Skudai, Johor
e-mail: cbasemaster@yahoo.com

Abstract
There are many issues and problems in the brain magnetic resonance imaging (MRI) area that haven’t solved or reached satisfying result yet. This paper presents an overview of the various issues and problems of the segmentation, correction, optimization, description and their application in MRI. The overview is started by describing the segmentation properties that are the most important and challenging in MRI brain manipulation. Then correction for reconstructing the brain MRI cortex, classification is utilized to classify the segmented brain image, and also review the uses of description is the great prospecting issue while some neurologist need the information resulted from brain imaging process including their potential problems from application applied by each technique. In each case, it is provided some general background information.

Keywords: brain MRI, issues, problems

1. INTRODUCTION
The presence of MRI has aroused the brain MRI visualization through image processing. Implementation of MRI visualization seems to be the recent important problems and issues in medical computer vision especially for the brain. The quantitative MRI brain structures examinations is becoming popular in study and medical area. The most problematic studies are overcoming the lack of boundaries, poor contrast, noise, supervised method, less robust, less efficient and less reliable to make a full use of obtaining data. Thus, it is expected that image processing methods will help to solve those problems.

Generally, brain MRI channels particularly are T1-weighted, proton density (PD), and T2-weighted data. While T1 data shows detailed anatomical brain image and T2-weighted data shows a less detailed anatomical brain image but have a high signal to detect lesions.

Digital brain MRI templates are able to measure signal changes in the brain that are due to neural changing activity. Due to that, it makes it possible to refine model by analyzing intensities of patterns as well as regions. However, past studies have never absolutely satisfied practitioners especially neurologist. There are many related problems and issues in different...
methods of neuroanatomical structures manipulations. In general, it is time consuming and a very delicate process. Thus, this paper will summarize the recent potential issues and problems in segmentation, localization, correction, classification, and description with most of which about segmentation.

2. SEGMENTATION

Basically, segmentation is a process of partitioning an image space into some non-overlapping meaningful homogeneous regions [1]. In general, these regions will have a strong relationship with the objects in the image. The success of an image analysis system depends on the quality of segmentation. In the analysis of medical images for computer-aided diagnosis and therapy, segmentation is often required as a beginning task processing. Medical image segmentation is a sophisticated and challenging task due to the intrinsically imprecise nature of the images. The result of image segmentation is a set of regions that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Some of the practical applications of image segmentation in medical imaging are: locating tumors and other pathologies, measuring tissue volumes, computer-guided surgery, diagnosis, treatment planning, and study of anatomical structure. For future research, MRI segmentation must strive toward improving accuracy, precision, and computational speed of segmentation algorithms, while reducing the amount of manual interaction needed while the recent methods can still be considered a supervised segmentation as guidance. There are variations of result and performance for semi-automatic and automatic segmentation that have been appeared nowadays. The potential offered improvements of MRI brain segmentation are such as:

a. The highly automated, robust, efficient and reliable to make a full use of the acquired data,
b. Replacing those methods with fully automatic expert systems,
c. Automated procedures that obtain high reproducibility and increase efficiency,
d. Extending distributed behavior-based multi agent system to more structures in brain images,
e. Utilizing co-segmentation to 12 weighted, flair or proton density,
f. Improving accuracy, precision, and computation speed of segmentation algorithms while reducing provided manual contribution,
g. Using a specific sigma for each volume depending of voxel intensity in using graph cuts segmentation algorithm,
h. Applying graph cut segmentation algorithm to subset of the full volume or even 2-d brain images.

Among the methods of MRI brain segmentation, clustering methods based on fuzzy set theory, such as Fuzzy C-means (FCM) algorithm, have been widely used for segmenting MRI data. Unfortunately, the conventional intensity based clustering algorithms are usually sensitive to the noise and intensity in-homogeneities influenced by the weakness of radio-frequency coil, which can leads to unsatisfactory segmentation results.

In medical imaging, the segmentation of MR brain images is an important problem. Although much effort has been spent on finding a good solution to the MRI segmentation problem, it is far from been solved [2]. This paper attempts to give an overview of the MR brain image segmentation problem and discusses various computational techniques for solving the problem.

Such studies typically involve vast amount of data. Recently, in many clinical studies segmentation is still mainly manual or strongly supervised by a human expert. The grade of operator supervision impacts the performance of the segmentation method in terms of time consumption, leading to infeasible procedures for large amount of datasets. Manual segmentation also shows large intra- and inter-observer variability, making the segmentation irreproducible and deteriorating the precision of the analysis of the segmentation. Hence, there is a real need for automated MRI segmentation tools.
2.1. Semi-automatic segmentation
The implementation of the semi-automatic segmentation algorithm on T2 axial volumes of the brain has been tested on six brain T2 datasets. All of which have been successfully segmented and could retrieve the contour of cerebellum, even it is unclear image [3].

2.2. Automatic segmentation
Automatic segmentation of brain magnetic resonance (MR) images clustered into the three main tissue types: white matter (WM), gray matter (GM), and cerebra-spinal fluid (CSF), is an area of great importance and much research. Many of methods applied are interactive, though efforts are being made to be replaced with fully automatic expert systems. It should be highly automated, robust, efficient and reliable in order to make a full use of the acquired data. However, supervised dividing of vast amounts of low-contrast/low-signal-to-noise ratio (SNR) brain data is severe work and is tend to large intraobserver and interobserver variability.

In order to get statistically significant result, a large number of data sets have to be segmented. Supervised or manual segmentation is getting questionable not only because of the amount of work, but also with regard of poor reproducibility of the result. The necessity of obtaining high reproducibility and the need to increase efficiency motivates the development of computer assisted, automated procedures. In other side, because of the presence of artifacts, classical voxel-wise intensity-based classification methods, such as c-means modeling and mixture of Gaussians modeling (e.g., [4] and [5]), may produce unrealistic results, with tissue class regions appearing granular, fragmented, or violating anatomical constraints.

Reviews on some methods for brain image segmentation (e.g., [6]) present the degradation in the segmentation algorithms quality because of such noise, and recent publications can be found addressing various aspects of these concerns. Currently, there is an opportunity to work on an extension of the model to incorporate intensity in-homogeneities as well as to support multichannel data [7].

The automatic segmentation of brain MR images, however, is still a persistent problem. Automated and reliable tissue classification is further sophisticated by overlapping of MR intensities of different tissue classes and by the presence of spatially smoothly varying intensity inhomogeneities. The automatic segmentation of MR images has been an area of intense study [8-9]. However, this task has proven problematic, due to the many artifacts in the imaging process.

3. CORRECTION
It is possible that procedure Brain masking from T1 MRI failed for one of the images. A solution may be provided by means the correction procedure which proposes variants of the standard one. The image registration coupled with genetic algorithm is used to predict the deformation of object. The inverse of this method is implemented to image and give the result that there are no slope with the probe.

The algorithm also mutual information used to predict deformation. Extensive experimental result on a set of brain MR images establish that the proposed method has been shown to remove the deformation and give the improved 3D reconstructions. The fig 1 (a-c) shows the input deformed image and their corresponding corrected images obtained through proposed image [10].

There is proposed an automated method to accurately correct the topology of cortical representations, adapted to the re-tessellation problem. The approach integrates statistical and geometric information to select the optimal correction for each defect. Iterative genetic operations generate candidate tessellations that are selected for reproduction based on their goodness of fit. The fitness of a re-tessellation is measured by the smoothness of the resulting surface and the local MRI intensity profile inside and outside the surface. The result of procedure is completely adaptive and self-contained. During the search, defective vertices are identified and discarded while the optimal re-tessellation is constructed.

Given a quasi-homeomorphism mapping from the initial cortical surface onto the sphere, that method will be able to generate optimal solutions. For each defect, the space to be

Issues and Problems in Brain Magnetic Resonance Imaging......... (Novanto Yudistira)
searched (i.e. the edge ordering) is dependent on the spherical location of the defective vertices. Some configurations of the quasi-homeomorphism mapping could lead to optimal but incorrect re-tessellations. In future work, addressing this limitation by directly integrating the generation of the homeomorphism mapping into the correction process is such a great plan.

Fig 1. The samples of deformed corrected images [10]

Deformable surfaces have also been used to generate topologically correct cortical surface representations. A parametric deformable surface model makes sure that the topology of the final surface is identical to that of the initial one. (Note that since a parametric surface can develop self-intersections, the topological correctness of the corresponding volume implied by the surface is still not guaranteed.)

The problem then becomes one of how to generate a topologically correct initial surface that is close enough to the cortex so that the deformable surface will correctly converge to the cortex. Fuzzy -means algorithm is used to get an initial segmentation of the white matter, which was then successively filtered with median filters until its is surface had the correct topology. There are two problems with this approach. First, it is not guaranteed to converge. Second, it changes the entire white matter volume when there may only be a local problem. We have found that this method can generate new handles, sometimes very large ones, while working to correct smaller handles in other regions of the volume.

Constructing and topologically correct representation of the cortical surface of the brain is a significant objective in various neuroscience implementations. Many cortical surface reconstruction methods either ignore topology or correct it using manual editing or methods that lead to inaccurate reconstructions. Recently, it is reported that fully automatic method yields a topologically correct representation with little distortion of the underlying segmentation. The authors provide an alternate approach that has several advantages over their approach, including the use of arbitrary digital connectivity, a flexible morphology-based multi-scale approach, and the option of foreground-only or background-only correction. A detailed analysis of the method’s performance on 15 magnetic resonance brain images is provided.

4. CLASSIFICATION

Fully unsupervised brain tissue classification from magnetic resonance images (MRI) is of great importance for research and clinical study of much neurological pathology imaging. The classification from the accurate segmentation of MR images into different tissue classes, especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF), is an important task [11].
In the medical usage, the ability to diagnose schizophrenia, epilepsy or Alzheimer’s disease systematically and quantitatively with MRI takes interesting developments not only to the study of the pathology. Some of the problems could be overcoming the supervised segmentation of 3D volumetric data that is difficult and time-consuming, and is tend to intra- and inter-rater errors.

Image classification has a purpose to convert spectral raster data into a finite set of classifications that represent the surface types seen in the imagery. These may be used to identify MR images properties especially in brain. Additionally, the classified raster MR image can be converted to vector features (e.g. polygons) in order to compare with other data sets or to calculate spatial properties. (e.g. area, perimeter).

MR Image classification is conducted in three different manners: supervised, unsupervised, and hybrid. In general, a supervised classification requires the manual identification of known surface features within the imagery and then using a statistical package to determine the spectral signature of the identified feature. The "spectral fingerprints" of the identified features are then used to classify the rest of the image. An unsupervised classification scheme uses spatial statistics (e.g. the ISODATA algorithm) to classify the image into a predetermined number of categories (classes). These classes are statistically significant within the imagery, but may not represent actual surface features of interest. Hybrid classification uses both techniques to make the process more efficient and accurate.

There is an important requirement in diagnosis that the need of magnetic resonance images according to region classification accuracy has been appeared. Performance and robustness of mixture model is getting worse when related with a variety of anatomical structure even though it has shown to give excellent result in automated segmentation of MR images of the human brain.

Accurate classification of magnetic resonance images (MRI) according to the tissue type or region of interest has become a urgent requirement in diagnosis, treatment planning, and cognitive neuroscience diagnostic tool in the research of the human brain. Changes in the composition of brain tissues can be used to identify and analyze physiological processes and largely characterize disease. For instance, changes in sulcal cerebrospinal fluid volume have been related to the neuro-degeneration hypothesis in schizophrenia. Measures of the amounts of gray matter (GM), white matter (WM), cerebrospinal fluid (CSF), as well as their spatial distribution, have been used to support diagnosis of degenerative brain illnesses like Alzheimer’s lesions. For detecting tissue abnormalities such as cancers and injuries, regions of interest (ROIs) are necessarilly utilized to be analyzed detail. In functional neuro-imaging there is the need to correlate brain structure and function.

The authors assume that the brain can be segmented into three basic constituent classes (CSF, GM, and WM) and two mixed classes CG and GW, where CG denotes a mixture of CSF and GM, and GW denotes a mixture of GM and WM. However, several studies indicate that a five component mixture model is still insufficient for modeling levels of intensity inhomogeneities and variability in tissues as a result of detailed biological processes. For instance, intensity histograms of abnormal brains show vast deviations from the intensity histograms of the normal population of brains that are used in the most automatic segmentation methods [12].

The result from segmentation evaluation [13], can be substantially improved if the form information of these structures probably can be incorporated into the decision making process. The weakness of the classification method is the requirement of varying parameter settings for different structures. In order to use this method extensively in clinical usage, standardization of the parameters is strongly required.

Accurate classification of MRI according to tissue type or region of interest has become a critical requirement in diagnosis, treatment planning, and cognitive neuroscience. Supervised segmentation methods are not suitable for vast amounts of data, and also are highly subjective and non-reproducible.

In the recent research of brain illness such as Alzheimer’s disease and schizophrenia, precise measurement of the amount of white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) and their spatial distribution is significant for quantitative pathological or clinical
analysis. Because of the advantages of MRI over other diagnostic imaging modalities, last
decades, there are many methods have been appeared for classifying MRI data.

5. DESCRIPTION

Identifying the anatomical structures in brain MRI is a great aspect of the preparation of
a surgical intervention in neurosurgery, especially when the lesion is located in eloquent cortex.
Particularly, the precise labeling or cortical structures surrounding the lesion is necessary to
determine the optimal surgical strategy, i.e. a strategy leading to the complete resection of the
lesion while preventing normal brain tissue and function.

Recently, the identification is purely based on the knowledge and experience of the
neurosurgeons anatomical. In practice, it may be more or less sophisticated, depending on
whether the region of interest is located near main anatomical landmarks (e.g. lateral sulcus,
central sulcus), and whether the normal anatomy is modified because of the presence of a
lesion. The general objective of the work actually is to support the surgeon in the identification
task, based on ontology about the brain cortex anatomical structures, represented in OWL, and
on a rule base capturing the dependencies between the properties of the brain cortex
structures. Another issue of the proposed approach is to partly automatist the annotation of the
semantic content of anatomical images.

Therefore, sometimes the segmentation result will be improved after utilizing the spatial
information that is probably resulted from description method. Many researchers are currently
working in this path [11].

The use of semantic description is great chance to make a description into MRI data
especially in brain images content. Labeling brain images content at the semantic level is
important for decision support in the context of neuro-imaging and neurosurgery, as well as for
producing images annotations that may support future retrieval. This paper shows how symbolic
methods can be used for the semantic description of the images, and the interest of combining
anthologies and rules for it. A simplified example illustrates the method proposed for assisting
the labeling of some brain structures in Magnetic Resonance Imaging.

The approaches exist in the literature, e.g. the SPAM approach (Statistical/Probabilistic
Anatomy Maps), in which anatomical knowledge is represented in an implicit way, in 3D object
maps obtained from large sets of brain data that were manually annotated, or segmented into
smaller volumes, after mapping individual’s datasets into the stereotaxic space. Probability
maps were then constructed for each segmented structure, by determining the proportion of
subjects that were assigned a given anatomic label at each voxel position in stereotaxic space.
The disadvantages of these methods are primarily: a poor modeling of the inter-individual
variability, and their incapacity when the brain presents a lesion. Our approach tries to
overcome these limitations. The great idea of this approach for the semantic description of the images based on ontology and rules that has been presented at the W3C workshop on Rule
Languages for Interoperability. The current paper explains some results of implementing this
idea utilizing the recent prototype reasoned.

As a part of the future work some spatial information will be incorporated while
segmenting the brain MR images. Because of the noise and intensity in-homogeneties
introduced in imaging process, different tissues at different locations may have similar intensity
pattern, while the same tissue at different locations may have a different intensity pattern.

Nevertheless, there is still a lack of actual clinical databases for validation purposes.
Much work is urgently needed in this avenue to systematically collect, annotate, and maintain a
set of real test images that enables detail and fair evaluation and comparison between different

The MRI is also provides rich three dimensional (3D) information about the human soft
tissue anatomy [14]. It reveals good details of anatomy, and yet is noninvasive and does not
require ionizing radiation such as x-rays. It is a highly flexible technique where contrast between
one tissue and another in an image can be varied simply by varying the way the image is made.
Applications that use the morphologic contents of MRI regularly require segmentation of the
image volume into tissue types. For instance, accurate segmentation of MRI of the brain is of
interest in the study of many brain diseases. In multiple sclerosis, quantification of white matter lesions is important for drug treatment assessment [15]. In schizophrenia, epilepsy or Alzheimer’s disease, volumetric analysis of gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF) is important to characterize morphological differences between subjects [16-21].

6. CONCLUSION

There are many issues and problems in the brain MRI area that haven’t solved or reached satisfying result yet. Solving the problems in order to boost the performance, improve the accuracy and the computation speed while reducing the amount of manual interactions are needed. The automatic processing of brain MRI remains a persistent problem. Automated and reliable tissue processing is further sophisticated by overlapping of MR intensities of different tissue classes and by the presence of spatially smoothly varying intensity in-homogeneities. The most problems in the beginning of brain MRI image processing are overcoming the noise and intensity in-homogeneities in imaging process. Because of that, it is possible that the procedure of processing for one of MRI images fails. The solution might be using some spatial information while processing the brain MRI.

In medical, a surgical intervention in neurosurgery preparation aspect is related with identifying the anatomical structures in brain MRI and greater advance in medical usage in order to support automatic or unsupervised brain MRI processing methods, especially when the lesion is located in around eloquent cortex. Particularly, the precise labeling or cortical structures surrounding the lesion is necessary to determine the optimal surgical strategy, i.e. a strategy leading to the complete resection of the lesion while preventing normal brain tissue and function.

REFERENCE


