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Proposed Magnetic Resonance Imaging for Brain Tumor Analysis

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ABSTRACT

The field of medical imaging has evolved rapidly in the recent years, leading to a wide variety of tools to image the brain. In particular, the resolution increases in Magnetic Resonance Images (MRI) techniques and allowed for better diagnosis and studies on the brain. Currently, different modalities of MRI have been widely exploited as state of the art for diagnosing brain tumors. However, they suffer from a number of shortcomings such as effective segmentation of the brain components into sub-compartments, noise acquisition from the equipment, ambient noise from the environment, presence of background tissue, other organs, breathing motion, and anatomical influences such as body fat. This study investigates different MRI techniques for brain tumor, and proposed a framework for analyzing tumor-bearing brain images automatically. The motivation behind this work is to increase patient safety by providing better and more precised data for medical decisions.

Key words: Magnetic Resonance Images, Brain Tumor Analysis, and Framework

INTRODUCTION

Medical image analysis is one of the most critical studies in the field of medicine. Medical imaging is the general name given to the group of techniques and processes developed for creating anatomical or functional images of human body, which are used for both clinical and scientific purposes [1]. Moreover, recent improvements in the imaging analysis and medical image processing provided a significant reduction in the requirement for crucial invasive intervention in treatment of various diseases or abnormalities [2].

Brain tumors are not a very common disease in the society, but are among the most fatal cancers. The causes of brain cancer are still largely unknown. However, the only environmental risk factors which could be identified so far, are exposure to certain chemicals or ionizing radiation [3]. Early detections of brain tumors are difficult because the brain is covered by the skull, and the tumors do not exhibit very specific clinical symptoms.

In general, three different categories of symptoms for brain tumors can be distinguished [4]: First, increased cranial pressure can lead to vomiting, headache and altered states of consciousness. Second, behavioural and cognitive impairment, personality or emotional changes can be attributed to brain dysfunction. And third, symptoms of irritation like fatigue, seizures or absences can be observed. However, all these symptoms are not specific for brain tumors only. Therefore, diagnosis usually starts with an interrogation of patient for medical history and symptoms. If a brain tumor is suspected, imaging plays a significant role. Currently, different modalities of Magnetic Resonance Images (MRI) have been widely exploited as state of the art for diagnosing brain tumors [5]. However, they suffer from a number of shortcomings such as effective segmentation of the brain components into sub-compartments, noise acquisition from the equipment, ambient noise from the environment, the presence of background tissue, other organs and anatomical influences like body fat, and breathing motion. Therefore, noise reduction is very important, as various types of noise generated limits the effectiveness of medical image diagnosis. The amount of the noise has the tendency of being either relatively high or low. Thus, it could harshly degrade the image quality and cause some loss of image information details [6].

Many application frameworks are developed in order to enable medical image data to be processed manually, semi-automated, or fully-automated by non-engineer field experts. However, effective use of many of these application domains requires a remarkable amount of manual interaction. This situation creates several negations such as difficulty in use and diversity on acquired results [6]. The motivation in this work is to increase patient safety by providing better and more precised data for medical decisions. The study investigates different MRI techniques for brain tumor and proposed statistical framework for analyzing tumor-bearing brain images automatically.

LITERATURE REVIEW

Medical image analysis for brain tumor studies is gaining attention in recent years due to an increased need for efficient and objective evaluation of large amounts of data. While the pioneering approaches applying automated methods for analysis of brain tumor images date back almost two decades. The current methods are becoming more mature and closer to routine clinical applications. This application of different medical imaging with the modalities are found in Ultrasound (used in cardiology, gynaecology, obstetrics, urology and neurology), X-Rays (for organ's identification such as skeletal x-ray, mammography and chest x-ray), Computed Tomography (used for detecting tumors, head infections and abdominal diseases), Magnetic Resonance Imaging (for soft-tissue analysis) and Nuclear Imaging (used in oncology and to diagnose Alzheimer's disease) [1]. The standard technique for brain tumor diagnosis was discussed in [1] [6].

Magnetic Resonance Imaging is a non-invasive technique, which provides good soft-tissue contrast [8] and is widely available in clinics. It can be used in a wide variety of settings, such as cardiovascular imaging [9] and musculoskeletal analysis [10]. In comparison to other techniques, MRI has the advantage of being almost completely harmless to the subject's health and allows for the distinction between soft tissues [5]. In addition, MRI produces images with high resolution, compared with the ones obtained through CT scans. Magnetic Resonance Imaging is used to create images of both surface and subsurface stationary structures, with a high degree of anatomical detail. In particular, the increase in resolution of MRI-based techniques allows for better diagnosis and studies on the brain. However, medical image segmentation remains a challenging problem, due to image complexity and absence of anatomical models that fully capture deformations in the brain structures [11], [12]. Hence, different MRI field strengths can affect segmentation results [13]. Manual segmentation methods are subjective, and it is common to find differences and variability between independent experts [14]. Therefore, several semi-automated and automated methods in brain tissue segmentation have been developed to alleviate these problems.

In this section, an overview of the state of the art medical image analysis for brain tumor studies is reviewed. It also provides a brief background on brain tumors in general and non-invasive imaging of brain tumors in order to give a comprehensive insight to the field.

Brain tumors are not very common, but among the most fatal cancers with an incidence of less than one hour in the western population [7]. A recent study estimated the US incidence rate for primary tumors of the brain or nervous system to be around 1 per 4,000 adults with approximately one-third of the tumors being malignant and the rest either benign or borderline malignant [15]. The word 'tumor' is of latin origin which means swelling. Today, a tumor is frequently associated with a neoplasm, which is caused by uncontrolled cell proliferation.

The first statistical analysis of MRI was proposed using multi-spectral data [16]. Since then, major developments have happened in the brain segmentation field [17-19]. The simplest method to segment brain tissues is manual tracing, which is subjective and time-consuming. Computer-based methods allow for faster and more objective tissue segmentations.

They are also more reliable, especially when dealing with pathological conditions [11], but do not always use all the information available. Several of these methods still rely on manual tracing to create ground-truth data or labels for segmentation. To avoid human intervention, other approaches have been developed to produce subject-specific automatic labels based on mixture models [20], clustering [21] or atlas registration [22].

Segmentation methods use several basic approaches which can be broadly grouped into data-driven, statistical analysis and neural or fuzzy networks. Data-driven methods were among the first methods developed to perform brain segmentation. However, they rely on intensity thresholds to detect the different tissues [23], especially when dealing with brain lesions [24]. Also, human intervention is required to set the thresholds, leading to subjectivity and loss of generalization. Moreover, the accuracy of these methods are limited and are very sensitive to noise. Statistical methods are among the most widely used approaches to perform brain segmentation techniques. Approaches based on the Expectation Maximization (EM) algorithm [25], non-parametric k-Nearest Neighbour (kNN) methods [26] and Support Vector Machines (SVMs) [20] [27]. The main disadvantage in most statistical approaches is the assumption of normal distributions which in the case of brain lesions, is seldom verified. The third main category of brain segmentation methods are the fuzzy and the neural networks. These cover a wide range of techniques ranging from Artificial Neural Networks (ANNs) [28] to fuzzy clustering [29]. The main issue for these classifiers is the excessive training time, as well as the careful selection of training data. Also, as with intensity based methods, noise presents many difficulties for segmentation.

Recent advances in MRI such as good contrast-to-noise ratios, whole-brain coverage and high spatial resolution, have led to an increased usage of brain atlases, with standard prior tissue probabilities [30]. The majority of modern brain segmentation methods register the images to segment to such atlases. In particular, most brain image segmentation software packages are atlas-based. The main drawback of employing atlas happens when significant anatomical changes occur due to brain lesions, regions with a high degree of variability occur in elderly people, with brain atrophy or in the case of infants. In such situations, it is difficult to establish the anatomy and number of tissues to be analyzed [31].

DISCUSSION AND COMPARISON OF TECHNIQUES

In this article, an overview of the state of the art medical image analysis for brain tumor studies is given. The focus was on segmentation and noise reduction methods for brain tumor modeling. The first attempts in this field were made almost two decades ago, but it can be observed in recent years that the methods are becoming mature and an increase of their use in clinical practice is expected.

The majority of segmentation approaches operate on multi-sequence MRI data, employing classification methods using different features and taking spatial information in a local neighbourhood into account. The advancement is not to segment the tumor only, but also to delineate tumor sub-compartments and different healthy regions on images from standard clinical acquisition protocols. This provides the physician with a more comprehensive information on which tumor monitoring, diagnosis and therapy planning can be based. Apart from the evaluation of accuracy and robustness, an important measure is computation time. Performing a better problem-oriented selection of the segmentation technique instead of choosing the technique first and then trying to make it work on the current problem. This could be accomplished in the future by paying more attention to feature selection than the segmentation algorithm.

The registration methods as a pre-processing technique can be separated into intra-patient registration and inter-patient registration. The main challenge of intra-patient registration is to handle effects of tumor growth, which is mostly done by tumor image-specific extensions to standard registration algorithms. The majority of inter-patient registration approaches focus on registration of tumor-bearing brain images with a normal atlas. This can be used for atlas-based segmentation or for constructing statistical brain tumor atlases. One attempt to handle the missing correspondence between healthy atlas and pathologic patient image is uniquely based on registration methods. A different idea is to combine tumor growth modeling with registration methods. While the registration approaches are more general, the integrated approaches tend to be more accurate. However, the tumor growth model adds additional complexity, which also introduces additional risks. A major problem, particularly for the integrated approaches, is their high computation time. Therefore, these methods should be considered as pure research methods currently, and will not reach clinical use until improvements in computational speed are attained.

When the traditional segmentation techniques and the atlas-based segmentation methods, which rely on registration are compared, it can deduced that, the traditional segmentation techniques are more flexible and can be easily adapted to handle multiple modalities simultaneously. Furthermore, it is possible to treat individual tumor sub-compartments more easily. Atlas-based methods have advantages when segmenting tissues, and structures surrounding the tumor, especially subcortical structures or functional areas. This can have important implications for surgery or radiation therapy.

However, many of the approaches incorporating tumor-growth modeling have difficulties in handling multifocal lesions. While preparing this proposal, it is observed that some researches in the literature lack precision, description of what exactly is being done, what type and grade of tumor are being considered, what image data is being used or how the algorithm performs in terms of robustness, accuracy and speed. More attention should be paid to differences according to the tumor type and grade, but also to robustness of the algorithm.

PROPOSED METHODOLOGY

The methodology employed for this study consists of Pre-processing, Feature Extraction, and Segmentation. Each of the modules consists of many algorithms and techniques. A deep investigation was carried out on suitable techniques to be employed for brain tumor analysis. A diagram illustrating the major steps used is shown in Figure 1.

A. Pre-processing

Most algorithms rely on some kind of pre-processing for image preparation and image enhancement. Many approaches have been suggested for the pre-processing task of MRI. The most popular and standard ones are image de-noising, intensity normalization and registration.

B. Feature Extraction

The features used for segmentation of brain tumors largely depend on the type of tumor and its grade because different tumor types and grades can vary a lot in appearance (e.g. contrast uptake, shape, regularity, location, etc.).

In addition, feature selection also depends on the sub-compartment of the tumor, which is to be segmented. The most common features used for brain tumor segmentation are Image Intensities, Mono-modal/Multi-modal, Alignment-based features, Edge-based features and Texture-based features.

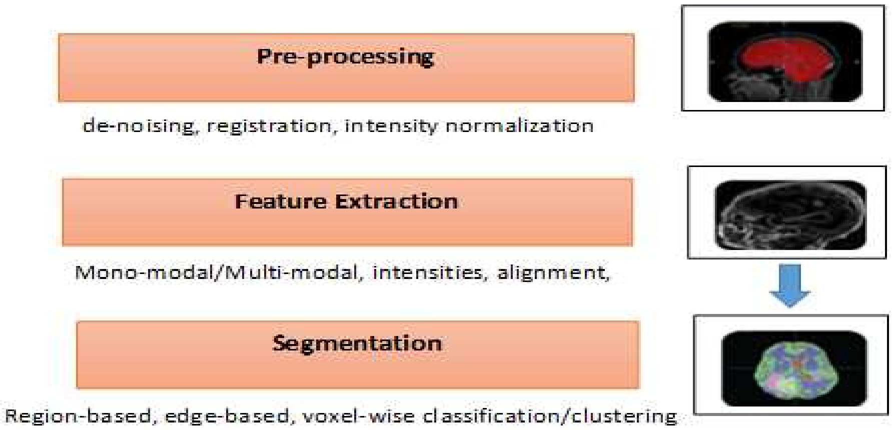

Fig. 1 Illustration of main modules for the proposed methodology

C. Segmentation

Based on feature extraction module, segmentation algorithms were categorized according to the features they use. Therefore, we distinguished the segmentation methods into region-based or edge-based methods, which mostly rely on deformable models, and classification or clustering methods, which make use of voxel-wise intensity and texture features.

EXPECTED OUTCOMES AND CONCLUSION

In general, evaluation and validation of results obtained are still challenging issue. The current standard relies on manual segmentations as a ground truth, however, these manual segmentations are not necessarily objective. Moreover, manual segmentation of MR images can yield the imaginable component of the tumor, whereas the complete extent of the tumor may be larger. Histological images are able to provide the complete information; these images are not available in most cases. Despite that, segmentation's algorithms will not be able to tell the complete truth, they should rather be regarded as a useful and objective tool, which can provide appropriate information to oncologists, clinicians and radiologists.

It is expected that the pre-processing steps which include de-noising, intensity normalization and registration can have a significant impact on the final result. Therefore, careful attention should be paid to these steps, and new improvements in these areas should be quickly incorporated into algorithms for analyzing brain tumor images. This does not only include attention to improvements in accuracy, but also speed and ease of user-handling.

Finally, it is anticipated that the results for segmentation are very promising in terms of accuracy, robustness and speed; also, the developed tools can be clinically used in the near future. It appears to be more difficult to accurately segment low-grade tumors than high-grade tumors. One reason for this might be enhancement and appearance pattern of high-grade tumors should be clearer and handled more reliable. Another reason might be simply that, the method was originally developed for high-grade tumors.

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