An image analysis approach to MRI brain tumour grading

Mohammadreza Soltaninejad[1], Xujiong Ye[1], Guang Yang[2], Nigel Allinson[1], Tryphon Lambrou[1]

[1]School of Computer Science, University of Lincoln, UK

[2]St. George's, University of London, UK

Introduction

Brain tumours are caused by abnormal and uncontrolled growth of cells inside the brain or spinal canal. They are the second cause of death relate to cancer in children and adults younger than 34 years [1]. The primary tumours are those started in the brain and are categorised in four main types: Gliomas, Meningiomas, Pituitary adenomas and Nerve sheath tumours. The most popular grading system for tumours is that suggested by the World Health Organization (WHO). Regarding to the WHO grading system, the tumours are graded from I to IV, corresponding to least advanced to the most advanced diseases, respectively.

Utilizing computer-aided procedures for medical diagnosis and treatment is a growing field of research nowadays. Among these procedures, medical image analysis plays a substantial role especially in cancer management [2]. The image processing application in cancer management includes prediction, screening, biopsy guidance for detection, staging, prognosis, therapy planning, and therapy response [3].

Depending on the imaging modality, images provide quantification measures alongside the visualization of the target tissue. Characteristics obtained from images such as location, size of the tumour, and imaging parameters [4] can be used for screening tasks in brain cancer. Whole-body MR imaging is another way of screening for cancer. In this method, metastasis that is caused by a tumour is monitored in other body organs. Research shows that MR imaging provides more accurate results for detection of metastases in comparison to other modalities [5].

Using diffusion weighted imaging is popular for investigating tumour response and allows early predictions of them [6]. However, conventional MR imaging can be used for prediction tasks in brain or other types of cancers. Kawahara et al. [7] investigated four different factors of T1 protocols and suggested that by combining them and using multivariate regression analysis is helpful for prediction of high-grade meningioma.

Medical image analysis research methods commonly consist of several parts, which use different algorithms in a sequence or a pipeline. Some pre-processing stages maybe used as to prepare the data for optimum results. These algorithms consist of segmentation, feature extraction and classification. Segmentation is based on visual characteristics of the images, which are related to their grey-level. Features are statistical measurements and information that can be extracted from a selected part of the image. Classification is the process of categorization the data based on their features which is a necessary stage for grading the tumours. These methods can be implemented independently as the main or as an auxiliary stage alongside with the main part of the algorithm.

Image processing and pattern recognition algorithms are widely used for analysis and interpretation of medical images. Feature extraction is the most important and impartible element of classification and pattern recognition tasks. In the case of medical images, such as MRI, the reduction of dimensionality is of high importance. MRI images are three-dimensional volumetric data acquired with different protocols, which lead to extraction of high dimensional information in the form of statistical features. Classification of high dimensional data is based on these extracted features.

Georgias et al. [8] utilized a pattern recognition system based on support vector machine classifiers and combination of features extracted form MRI images and spectroscopy ratios. Their method efficiently discriminates between meningioma and metastatic brain tumours. Zacharaki et al. [9] performed a comprehensive assessment of pattern recognition methods on detection of different types of brain tumours and grading gliomas based on WHO grading system. They used a set of different image features including: intensity, shape, statistical characteristics and texture. Regarding to the high dimensionality of the feature space, they used feature selection methods to find an optimum feature subset.

Angelini et al. [10] proposed a differential analysis system to measure the growth of low-grade glioma in MRI brain images. Joshi et al. [11] developed a system for detection of Astrocytoma cancer tumours and classify them based on artificial neural network. Georgiadis et al. [12] proposed a method to classify primary and metastatic tumours, which originated outside the brain. Soltaninejad et al. [13] proposed a framework for classifying different tumour grades exploring information from several MRI acquisition protocols, see figures 1 and 2 for the algorithmic layout and initial results.

MRI Brain Tumour Imaging and Analysis

MRI is the most commonly used imaging modality for brain tumour assessment [14], as it provides efficient evaluation of tumour analysis and the acquisition is non-invasive [15].

Segmentation in medical images means partitioning the pixels to detect and separate the target area usually a tissue or a lesion. In some research fields, segmentation of a specific tissue or tumour is the main purpose. In others, segmentation is an intermediate stage for further analysis such as classification or other measurements. For the case of brain tumours, it is a difficult task regarding to the characteristics of the tumour in the MR images [15]. The first stage in most medical image processing research is pre-processing. The most popular pre-processing method is noise suppression or correcting for non-uniformities. There are several algorithms proposed for this task that beside their benefits, they may have negative effects on further processing stage [16]. Before any analysis on a specific target in the image, it is necessary to segment that from other parts in the image. Image segmentation algorithms use edge, region or intensity properties of the target tissue in the image to separate them from the background [17]. The aim of edge-based segmentation methods is to find the boundary of two adjacent regions that have different characteristics. One of the most popular algorithms for detection of tumour edges in MRI images is using level-sets [18] and/or combining it with classification or clustering methods [19]. In our work [13], we use the properties from sub-regions of the image. These sub-regions are grouped together based on their similar characteristics and their spatial adjacency. The image is segmented to small partitions using a linear iterative clustering superpixel (SLIC) algorithm [20]. Superpixels are groups of pixels with similar features.

Feature extraction

Feature extraction is a step used for both segmentation and classification of tissues in medical images. Since the tumours have different types and grades and there are different acquisition protocols, the tumour region in the image may have different properties. So, a wide range of feature types can be used in image analysis of brain tumours [15]. Intensity features are most popular in this field. The idea is that tumours have different intensity in comparison to other healthy tissues. Several statistical measures can be calculated from the pixels of the target area in the image. The other common features are based on textural patterns [22], as different tumour regions have specific textures. Fractal-based features are also used for brain tumour segmentation and detection [23], as well as context features for segmentation in MRI brain images [24].

The features may be extracted from a single MRI acquisition protocol [25] (i.e. FLAIR, T1-weighted, T2-weighted, etc.) or using different protocols together [26]. Even combinations of features from different modalities are investigated [27]. However, such strategy dramatically increases the number of features acquired, and to overcome this, the employment of feature selection methods for choosing an efficient set of them with the highest classification accuracy [28] should be considered.

Classification for grading

Classification in machine learning means finding a model, based in a set of training data, in order to categorize a general set of data. Classification algorithms can be used in supervised segmentation of MRI images [29]. Automatic brain tumour segmentation methods often use this type of segmentation [30]. Some further analysis tasks for medical images are also involved with classification. One of them is grading the tumours based on their type, which is also called tumour grading. The data for training the classification model are the features that are extracted from the images. Each feature vector has a label corresponding to the tumour type. The aim of classification is to find the class labels (i.e. tumour types) for the new images. Several classification methods are used for this purpose. A popular classification method in many medical applications is Support Vector Machine (SVM) that is used for brain tumour classification [9]. This method is suitable for two classes and can be extended for multiclass cases. In [31] a method is suggested based on combination of Neural Networks and Principal Component Analysis (PCA) for reducing the feature space and providing a more robust classifier. In [13] we investigated the application of a linear support vector machine classifier using datasets from different MRI imaging protocols in order to differentiate tumour grades II, III and IV. The assumption to use several protocols rather than a single approach is to obtain more information for training the classification system. Another issue we investigated is using multiple superpixel features from these protocols to assess their efficiency for classification. By increasing the feature space, it seems that advanced classification techniques should be utilized to improve the grading task.

Discussion and outlook

Image analysis and computer vision techniques are widely used for detection and grading the tumours in medical images. Due to developments in imaging and processing techniques, using the state-of-the-art pattern recognition and computer vision in advanced imaging modalities with multi-modal approach attracts the most attention in today's research.

The variety of issues and complexity of brain in MRI images had made it a challenging task to perform automated image analysis. The current brain image analysis methods, due to their long computational time, are mostly confined in research-focused institutions, and are not applicable for generic clinical usage. Most of them are for specific imaging protocols that target specific lesion types, and usually are tested on a relative small group of data.

Any proposed automated MRI brain tumour segmentation/grading system should consider the real-world issues and be acceptable by the physicians for everyday use. Data that is used for training such systems should come from multi-centre collaborations and try to cover as many different imaging protocols, tumour types, and grades, as possible. The provided solutions besides being efficient in terms of speed, accuracy, and robustness, they also should be comprehensive and standardized. The challenge remains for state-of-the-art computational techniques to bridge the gap between research oriented implementations and clinical routine applications.

Acknowledgment

This research was supported by European FP7 collaborative project “MyHealthAvatar” (600929). Dr. Yang was sponsored by Cancer Research UK; (C1459/A13303). Data were obtained during the EU FP7 “eTUMOUR” project.

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