Abstract

Glioma is the most common primary brain tumor in human beings. Median survival time of primary glioblastoma (which is a Grade IV glioma) is a dismal 15 months with surgery, radiotherapy and chemotherapy as reported by WHO in 2016. The goal of this thesis was to develop a methodology for accurate diagnosis and treatment planning of glioma patients using conventional and dynamic contrast enhanced (DCE)-MRI using a machine learning framework. At first the methodology for computing robust DCE-MRI parameters were standardized. Then the study focused on segmentation of glioma followed by classification of glioma into various grades. Each of this work viz. quantification of robust DCE-MRI parameters, segmentation of glioma and grading of glioma had certain challenges which I have tried to address through this research work.

The first part of my thesis work establishes that $B_1$ inhomogeneity can create significant error in DCE-MRI data analysis using *in vivo* brain data as well as simulated data. Then it was shown that this error can result in erroneous grading of glioma patients under certain conditions using simulation studies on *in vivo* data. Finally, some simulation studies showed that choosing an optimal flip angle in DCE-MRI protocol can largely reduce $B_1$ inhomogeneity related errors.

The differentiation between vasogenic edema and non-enhancing tumor (NET) within glioma is difficult as both are hyperintense on conventional images. It was also found that there is inter-radiologist differences in delineating the ground truth for NET and vasogenic edema. The second work in my thesis proposed a methodology to differentiate between vasogenic edema and NET in
high grade glioma using DCE-MRI parameters. This work also proposed a method to reliably obtain the ground truth using pre and post-surgery MRI images.

Differentiating between intermediate grades of glioma (Grade II vs. Grade III and Grade III vs. Grade IV) is challenging as they have many overlapping characteristics. The third work in my thesis attempts to differentiate between intermediate grades of glioma as well as multiple grades (Grade II vs. Grade III vs. Grade IV) using DCE-MRI parameters combined with volume of tumor components under a machine learning framework. The work concludes with the fact that an optimal feature set should be used to obtain low misclassification error as it uses complimentary information.

The work in the thesis tried to provide some insights into how $B_1$ inhomogeneity can effect DCE-MRI data analysis and emphasized the need of inhomogeneity correction in tumor grading. The major contribution in the segmentation work was the proposal of an alternative way of finding the ground truth for tumor segmentation to that of radiologist delineation of tumor subparts. The major contribution of the grading work was the optimization of features for maximizing classification accuracy in a machine learning framework. The proposed methodology in the thesis can result in a GUI based software tool which automates the process of segmentation and grading for glioma patients. The author believes that the work in the thesis can potentially help doctors in better diagnosis and treatment planning of glioma patients.