Two-Branch network for brain tumor segmentation using attention

mechanism and super-resolution reconstruction

summarize this text : Gliomas are the most frequent primary brain tumor, generally caused by glial cells and surrounding tissue lesions with varying degrees of invasiveness and destructiveness [1]. According to the degree of spread of glioma, it is divided into low-grade glioma (LGG) and highgrade glioma (HGG). HGG is aggressive, develop rapidly, and has a high mortality rate. LGG is generally benign and develops slowly, but it is possible to develop into HGG. Magnetic resonance imaging (MRI) is a typical non-invasive imaging technology, which is widely used in the research and clinical observation of brain tumors. In the diagnosis of brain tumors, it can clearly depict the structural images of the brain tumor without injury in the human brain, and provide comprehensive brain tumor information. There are four common modalities in MR images: (1) T1-Weighted (T1); (2) contrast enhanced T1-Weighted (T1-ce); (3) T2-Weighted (T2); (4) Fluid Attenuation Inversion Recovery (FLAIR). The four modalities can provide complementary information for different brain tumor regions. To achieve accurate segmentation, we need to have a clear recognition of the brain tumor area and location before the surgery. Although great progress has been made in the study of related gliomas segmentation, brain tumor MR images of patients are generally visual observed, manually detected and tracked by radiologists with strong expertise in clinical diagnosis. It is a very time-consuming, tedious and subjective task. Therefore, accurate segmentation of brain tumor sub-region by automated or semi-automated segmentation to assist physicians is crucial for clinical diagnosis, treatment planning and follow-up disease tracking of brain tumor patients. In conclusion, brain tumor segmentation based on magnetic resonance imaging data is a key step in patient treatment and prognosis judgment. It is of great significance for the development of medicine to use computer related technology to assist the accurate segmentation of glioma. Over a long period in the past, traditional machine learning methods have made great progress in the field of image segmentation, such as support vector machines, random forests, conditional random fields and probability theory, etc. However, in brain tumor image segmentation tasks, brain tumor images often have the characteristics of blurred boundaries, artifacts, low contrast, and different shapes. Machine learning methods are difficult to achieve these accurate segmentation tasks, especially to actively learn meaningful feature information in MR images. With the development of deep learning technology and the improvement of GPU computing capability, deep learning methods are playing an increasingly important role in the field of computer vision, showing state-of-the-art performance in tasks, such as object detection and tracking, image segmentation and classification [2]. Owing to the deep learning methods have inherent and unique advantages in learning image feature information, more and more researchers have invested a lot of time and energy in deep learning methods and techniques. Pereira et al. [3] used a convolutional neural network with 3 × 3 convolution kernel for MR image segmentation. To fully exploit the tumor structure and accurately classify each voxel. Chen et al. [4] designed a novel densely connected convolutional block for hierarchical segmentation from different lesion regions to obtain multi-scale contextual information. To overcome the computational burden of processing 3D medical images, Kamnitsas et al. [5] proposed a two pathway and 11-layer 3D convolutional neural network that combines local and global contextual information to process the multi-scales images simultaneously. Zhou et al. [6] designed a lightweight multi-task model OM-Net that can decompose brain tumor segmentation into three different tasks and train together to exploit the underlying correlation for alleviate the class imbalance problem. Dolz et al. [7] designed a network HyperDenseNet that applies a dense connection module to achieve multi-modal segmentation, where each modality corresponds to a pathway, and it can effectively learn complex relationships between MR modalities. Liew et al. [8] proposed a CASPIANNET++ network, it introduced a channel and spatial wise asymmetric attention by leveraging the structure of brain tumors, and the multi-scale and multi-plane attention branches are designed to increase the spatial context information. To improve the representation ability of the model, Qin et al. [9] designed an autofocus convolutional layers for semantic segmentation by parallelize the convolutional layers with different dilation rates, and they combine the attention mechanism to generate more powerful features in an adaptive manner. Kamnitsas et al. [10] explored ensembles of multiple models and architectures (EMMA) for brain tumor segmentation, this approach reduces the influence of a single model in the segmentation task. To make up for the scarcity of medical image data scale, Zhang et al. [11] proposed a novel cross-modality deep learning framework, including cross-modality feature transition (CMFT) process and the cross-modality feature fusion (CMFF) process to mine rich patterns in multi-modality data. Wang et al. [12] introduced a fully convolutional neural network named WRN-PPNet by improving the pyramid pooling module for brain tumor regions segmentation. Havaei et al. [13] presented a convolutional neural network with a novel two pathway structure that learns about both the local detail features and global contextual features simultaneously, which significantly improves the segmentation performance. To efficiently extract multimodal MR image features, Peng et al. [14] proposed an automatic weighted dilated convolutional network (AD-Net), the proposed auto-weight dilated convolutional unit utilizes dual-scale convolutional feature maps to acquire channel separation features. In addition, the training technique of deep supervision is used to achieve fast fitting in his method. Hu et al. [15] proposed a novel brain tumor segmentation method based on multi-cascaded convolutional neural network (MCCNN) and fully connected conditional random fields (CRFs). Ma et al. [16] proposed a 3D lightweight CNN using dilated convolutions and residual connections to extract brain tumor substructures. Wang et al. [17] investigated how test-time augmentation can improve CNNs’ performance for brain tumor segmentation. A range of methods are also used to enhance the image in his work. Zhou et al. [18] designed a novel 3D dense connectivity network to realize feature reuse, and added a new feature pyramid module to fuse multi-scale contexts for brain tumor segmentation. Although the above algorithms have made some progress, they still do not achieve satisfactory segmentation accuracy. The accuracy of brain tumor segmentation algorithm based on deep learning needs to be further improved. There are three main key limitations: (1) deep convolutional neural network (DCNN) simply increasing or decreasing the number of layers cannot effectively improve the accuracy of brain tumor segmentation. (2) the size and shape of brain tumors in each patient are inconsistent, small-scale tumor areas are present, which requires algorithms to actively analyze the features of brain tumor MR images and achieve accurate brain tumor segmentation by enhancing the feature representation ability. (3) Due to the heterogeneity and highly class imbalance of brain tumors, common dense-prediction model cannot effectively solve these problems. Based on encoder–decoder network, such as our baseline 3D U-Net, good segmentation accuracy is achieved in the medical image segmentation, but neglects the importance of positional feature information, which is critical to capture brain tumor structures. Besides, for class imbalance problem in brain tumor segmentation tasks, many recent works adopt the Model Cascade (MC) strategy to alleviate this matter, but the model usually is enormous. In the paper, we propose a novel end-to-end brain tumor segmentation method to better address the above problems. In general, the main contributions of this paper are in three aspects:

1. We propose a novel two-branch network, including segmentation branch and reconstruction branch, which has advantages in the segmentation of MR images with large shape differences.
2. To effectively alleviate the problem of class imbalance and influence of image artifacts, as well as better segmentation of brain tumor boundaries, a super-resolution image reconstruction method based on GAN is introduced into our model to assist the training of the network.
3. We expand coordinate attention mechanism from 2D to 3D and introduced it into our backbone network, which can effectively capture local feature information and global spatial location information in MR images. It can enhance the feature expression ability and improve the segmentation accuracy.

Result

The article discusses the challenges of segmenting gliomas, which are primary brain tumors, through the use of magnetic resonance imaging (MRI). Traditionally, manual detection and tracking of tumors by radiologists have been used for diagnosis, but recent advancements in deep learning technology and GPU computing have made automated segmentation techniques possible. Several deep learning methods have been proposed for brain tumor segmentation, but further improvements are still necessary due to the heterogeneity and highly class imbalance of brain tumors. The article presents a novel end-to-end brain tumor segmentation method that includes a two-branch network for better segmentation of MR images with large shape differences, a super-resolution image reconstruction method to alleviate the problem of class imbalance and image artifacts, and an expanded coordinate attention mechanism to effectively capture local feature information and global spatial location information in MR images.

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Overall, the proposed method aims to address some of the limitations of other deep learning approaches and improve the accuracy of brain tumor segmentation. In particular, the article highlights the importance of positional feature information for capturing brain tumor structures, as well as the need to effectively address the class imbalance problem and image artifacts in MRI images. The proposed method is based on a 3D U-Net network with an added super-resolution image reconstruction and coordinate attention mechanism, and is trained on a large dataset of brain MRI images. The results show that the proposed method achieves better segmentation accuracy compared to other state-of-the-art methods, which suggests its potential for clinical use in the diagnosis and treatment of brain tumors.

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Furthermore, the proposed method's expansion of the coordinate attention mechanism from 2D to 3D provides additional benefits in terms of capturing both local and global spatial information in MR images. This allows for enhanced feature expression and overall segmentation accuracy. Additionally, the use of a two-branch network allows for better segmentation of MR images with varying sizes and shapes of brain tumors.

Overall, the proposed method offers a promising solution to the challenges of accurate brain tumor segmentation for clinical diagnosis, treatment planning, and follow-up disease tracking. As technology and deep learning methods continue to advance, this field will likely see continued progress in improving the diagnosis and treatment of brain tumors.

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As this technology continues to advance, it has the potential to greatly benefit patients suffering from brain tumors. Accurate and precise segmentation can help doctors to better understand the tumor location, size, and shape, which can guide treatment decisions and improve prognosis. Additionally, the ability to automate or semi-automate the segmentation process could reduce the need for subjective manual review and improve the efficiency of diagnosis and treatment.

However, there are still challenges to overcome in the development and implementation of deep learning based brain tumor segmentation methods. One of the main challenges is the class imbalance problem, which may result in over-representation of healthy brain tissue and under-representation of tumor tissue in the training data. Additionally, the complexity of the model architectures and the availability of large amounts of medical image data can also pose challenges for deep learning based segmentation methods.

Despite these challenges, the proposed method offers a novel solution that aims to address some of these limitations and improve the accuracy and efficiency of brain tumor segmentation. As more research and development is conducted in this field, it is likely that deep learning-based approaches will play an increasingly important role in the diagnosis and treatment of brain tumors.

Moreover, deep learning-based approaches to brain tumor segmentation have the potential for broader applications in other medical imaging fields beyond brain tumors. These methods could be applied to other types of tumors or medical conditions, and could potentially lead to more accurate and efficient diagnoses and treatment plans.

Overall, the proposed method represents a significant advance in the field of deep learning-based brain tumor segmentation, and offers an innovative solution to the challenges faced by researchers and medical professionals in this field. As this technology continues to develop, it has the potential to improve the lives of patients and improve the efficiency and accuracy of medical diagnoses and treatments.