CONCLUSIVE SURVEY ON BRAIN REGION SEGMENTATION USING CONVOLUTIONAL NEURAL NETWORK

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Abstract*—In this paper,Brain region segmentation or skull stripping is an essential step in neuro imaging application such as surgical, surface reconstruction, image registration etc. The accuracy which has to be find of all existing methods depends on the registration and image geometry. When this kind of method fails, the possibility and probability of success is very less. In order to ignore this, Convolutional Neural Network (CNN) is used. For brain extraction which is free from geometry and registration. CNN learned the together connectedness and shape of the brain. OASIS database is used which is publicly available benchmark dataset. In this method, training phase uses 30 images and 10 images are used for testing phase. The performance of CNN results is closer to the basic level true results given by experts. Further, the target is to add some more calculative features to the existing CNN technique in order to improve the parameter evaluation processes.

Keywords*— Brain region segmentation, skull stripping, MRI, convolutional neural network.

I. INTRODUCTION

Many of theprocedures have been developed for brain region segmentation. Noise and Intensity are in similarityhave two main obstacles. As a result, noise removal is to be taken into consideration before further analysis of images [1]. Non Local Mean filter algorithm is developed in order to remove the Rician noise [2]. A new similarity measure is used to clear out the Rician noise based on that pixel value [3]. 3D convolutional neural network is used for brain region segmentation method [4]. Fully convolutional networks are trained in two ways one for patch wise prediction and another one for supervised pretraining [5].

Mohammad Havaei et al, [6] proposed CNN; it is different from digital image processing techniques. It uses both local features and global context-specific features simultaneously. 2- phase training method is described in this review paper; it is easy to predict the tumor labels. It improves the speed 30 times faster ang quicker than state of the art method. Deep learning method provides most accurate results. This procedure is more efficient(not time consuming) and it evaluate large amount of data in MRI images [7]. The brain tumor segmentation is mainly focused and attentive on network architecture and it learns complex and difficult feature from the data itself. It is based on both discriminative and generative model. Discriminative method learns the correlation between the input image and ground or basic level truth image and it mainly depends upon feature extraction. Generative models are used to extract the tumorcells. 3D CNN architecture is used for multimodality glioma segmentation task [8]. The cube of voxels ,pixels and patches are extracted from MRI images, this is used as an input of the method. In this paper CNN is used to predict the tissue label from cube of voxel. For accurate and high resoluted brain lesion segmentation, 3D Convolutional Neural Network (CNN) is used, which is proposed by Konstantinos Kamnitsas [9]. Input image is processed and carried out at multiple scales simultaneously by using dual pathway architecture. By classifying each voxel in an image it takes the neighborhood, i.e. local and contextual information into account and it is estimated by voxel wise method. This is achieved by using sequential convolution of the input at the cascaded network and it reduces false positive rate. Deep CNN uses small convolutional kernels for glioma segmentation [10].

For more convolutional layer, it has been using small kernel while having the same receptive field of bigger kernels. It has two 3×3 cascaded convolutional layers have the same effective receptive field for 5×5 layer but fewer weights. One of the advantages of using the method is to reduce the overall fitting because smaller kernel has fewer weights than bigger kernel. Olaf Ronneberger [11] shown convolutional network for biomedical image segmentation. This architecture consists of contracting path and symmetric expanding path. Contracting path is used for capture context and expanding path is used for precise localization. This network can be trained end-to-end from very few images and outranges the prior best method (a sliding window convolutional network) for segmentation. This architecture has two 3×3 convolutional layer, in each layer ReLU function is applied. The number of feature channels is doubled at each down sampling step. Every step in the expanding path contains of an up sampling of the feature map, it reduces the number of feature channels. At final layer, soft max classifier is used for classifying different classes. The application of convolutional layer consists in convolving a signal or an image with kernels to obtain feature maps [12]. In training phase, the weights of the kernels change adaptively,done by back propagation, in order to enhance the input. Usage of several-cascaded CNN architecture has been introduced as well as proposed to increase the flexibility and speed of computation for medical image segmentation. In every layer, the output of the first layer is mixed with the input of the second layer. It is used to learn the context information in CNN network. Pixel class prediction is learned from all CNNs. The predictions made are regularized using a more global super pixel segmentation of the image.

In this work, MRI images are used. In pre-processing step, the Rician noise is reduced by using Non Local Mean (NLM) filter algorithm. Brain region segmentation is a major step in brain imaging applications before doing main processing and it refers to the removal of non-cerebral tissues like skull. From the denoised image, brain region is segmented by using Convolutional Neural Network.

II. LITERATURE REVIEW:

Vovk U. and Likar B.,

Medical image processing devices are majorly used to provide a large amount of anatomical and functional information which improve diagnosis and patient treatment especially by modern techniques to analyse the medical images. However, mode specificity of image objects like the phenomena of intensity in homogeneity in magnetic resonance images (MRI), are still in known and can unfavorably affect quantitative image analysis. In this paper, many methods that have been introduced and used to reduceintensity in homogeneities in MRI are reviewed. First, the methods are being specifiedin accordance with the in homogeneity correction strategy. Next, different qualitative and quantitative evaluated approaches have been reviewed. Third, 60 relevant publications are categorized in accordance with the several features and examined so as to reveal major trends, evaluation strategies and applications. Finally, key evaluation issues and future development of the in homogeneity correction field, supported by the results of the analysis, are discussed.

Furthervision into the field of intensity in homogeneity correction was provided by a detailed analysis of numerous publications that appeared in the last two decades. A number of important issues are considered, indicating that intensity in homogeneity correction is still not a completely solved problem. Because of this and also because of the evolving MRI technology and associated applications, the problem of intensity in homogeneity correction will certainly continue to receive a lot of scientific attention in the future. Besides, validation issues should receive much more attention than in the past.

Bin Liua b, XinzhuSanga, ShujunXinga, Bo Wangaa.,

Combination of Non-Local Mean filter with exact fuzzy cluster criteria, denoising in synthetic brain Magnetic Resonance Imaging are being considered.The various experiments show that the noise is efficiently suppressed and image details are well preserved as in comparison to the wavelet method. Quantitative and qualitative results indicate that the continuous advantage and detailed structure are well kept, objects are greatly abridged and brain MR images are typically enhanced. In addition, the computational time is reduced greatly.

Non-local means (NLM) is a patch based image denoising method which damages the natural structural usefulness in a noisy image to restore higher quality image. Here, a combinations of the method of non-local means and fuzzy cluster have been shown for brain MRI denoising. Quantitative and qualitative results have been compared with the NLM denoising method and wavelet method, and results show that our proposed method can not only clears the noise more effectively but also keep it well the continuous edge and detailed structure for brain MRI. In addition, the computational time is reduced greatly. A problem to be resolved is the automatic selection of NLM parameters according to the medical image. In our experiment, default values of NLM method are used and good image quality is gained.

Sudipto Dolui, Alan Kuurstra, Iván C. Salgado Patarroyo, Oleg V. Michailovich.

In this paper, the application of non-local means (NLM) filtering on MRI images have been conducted. An importantcomponent of any NLM-based algorithm is its similarity measure used to compare woxel intensities. Unfortunately, virtually all existing similarity measures used to denoise MRI images have been derived under the assumption of additive white Gaussian noise contamination. Since this idea is well- known to fail at low values of signal-to-noise ratio (SNR), alternative formulations of these measures which take into account the correct (Rician) statistics of the noise are required. Basicaly, the most important contribution of the present work is to introduce and develop a new similar measure for NLM filtering of MRI images, which is derived under bona fide statistical assumptions and proves to focus important theoretical advantages over alternative formulations. The utility and feasibility of the proposed method is executed through a series of numerical experiments using both in silico and in vivo MRI data.

Sudipto Dolui, Alan Kuurstra, Iván C. Salgado Patarroyo, Oleg V. Michailovich.

The present paper has projected two novel NLM-based methods for augmentation of MR images.More specifically, the paper introduced two new definitions of the NLM similarity measures, which take into account the true Rician statistics of measurement noises. In addition, the closed form expressions accordingly to these similar measures have been derived for the case of MRI noise. In a further process step by step, the proposed similarity measures have been shown to focus several favorable characteristics for the purpose of denoising of MRI images. Furthermore, some key theoretical connections have been pointed out between the similarity measures. Finally, the utility of the proposed algorithm has been demonstrated through a series of computer simulations and real-life experiments. Based on the obtained results, one can find that the proposed algorithm has been able to provide better reconstruction results as compared to a number of established reference approaches.

Jens Kleesiek, Gregor Urban, Alexander Hubert, Daniel Schwarz, Klaus Maier-Hein, Martin Bendszus, Armin Biller,

Brain removal from magnetic resonance imaging (MRI) is crucial for many neuroimaging workflows. Current methods demonstrate good results on non-augmented T1-weighted images, but struggle when opposed with other modes and medically altered tissue. In this paper we present a 3D convolutional deep learning architecture to address these shortcomings. In contrast to existing methods, we are not limited to non-enhanced T1w images. When trained exactly, the approach handles an imaginary number of modes including contrast-enhanced scans. Its applicability to MRI data, comprising four channels: non-enhanced and contrast-enhanced T1w, T2w and FLAIR contrasts, is demonstrated on a challenging clinical data set containing brain tumors (N = 53), where our approach outperforms six commonly used tools with a Dice score of 95.19.

Jonathan Long, Evan Shelhamer, Trevor Darrell,

Convolutional networks are impactful visual models that seizes hierarchies of features. We show that convolutional networks themselves, trained end-to-end, pixels to-pixels, cross the limit of the state-of-the-art in semantic segmentation. Our key vision is to build “fully convolutional” networks that take input of imaginary size and produce correspondingly-sized output with effective inference and learning. We define and detail the space of convolutionalnetworks, explain their application to spatially solid prediction tasks, and draw connections to prior models.

Fully convolutional networks are a rich class of models, of which modern classification convnets are a special case. Recognizing this, extending these classification nets to segmentation, and improving the architecture with multi-resolution layer combinations dramatically improves the state-of-the-art, while side by side simplifying and speeding up learning and inference.

Mohammad Havaei, Axel Davy, David Warde-Farley, Antoine Biard, Aaron Courville, YoshuaBengio, Chris Pal, Pierre-Marc Jodoin, Hugo Larochelle,

In this paper, we present a fully automatic brain tumor segmentation method based on Deep Neural Networks (DNNs). The proposed networks are bespoke to glioblastomas (both low and high grade) pictured in MR images. By their very nature, these tumors can be seen anywhere in the brain and have almost any kind of shape, size, and contrast. These reasons takes our exploration of a machine learning solution that destroys a flexible, high capacity DNN while being extremely efficient. Here, we give a description of different model choices that we've found to be necessary for obtaining competitive performance. We explore in particular different architectures based onConvolutional Neural Networks (CNN), i.e. DNNs majorly adapted to image data. We present a novel CNN architecture which differs from those traditionally used in computer vision. Our CNN exploits both localfeatures as well as more global contextual features simultaneously. Also, different from most traditional uses of CNNs, our networks use a final layer that is a convolutional implementation of a fully connected layer which allows a 40 fold speed up.

Ali Isin, cemDirekonglu, MelikeSah,

Brain tumor segmentation is an important task in medical image processing. Early diagnosis of brain tumors plays an important role in improving treatment possibilities and increases the survival rate of the patients. Manual segmentation of the brain tumors for cancer diagnosis, from large amount of MRI images generated in clinical routine, is a difficult and time consuming task. There is a need for automatic brain tumor image segmentation. The purpose of this paper is to provide a review of MRI-based brain tumor segmentation methods. Recently, automatic segmentation using deep learning methods proved popular since these methods achieve the state-of-the-art results and can address this problem better than other methods. Deep learning methods can also enable efficient processing and objective evaluation of the large amounts of MRI-based image data. There are number of existing review papers, focusing on traditional methods for MRI-based brain tumor image segmentation. Different than others, in this paper, we focus on the recent trend of deep learning methods in this field. First, an introduction to braintumors and methods for brain tumor segmentation is given. Then, the state-of-the-art algorithms with a focus on recent trend of deep learning methods are discussed. Finally, an assessment of the current state is presented and future developments to standardize MRI-basedbrain tumor segmentation methods into daily clinical routine are addressed.

Automatic segmentation of the brain tumors for cancer diagnosis is a challenging task. Recently, availability of public datasets and the well-accepted BRATS benchmark provided a common medium for the researchers to develop and objectively evaluate their methods with the existing techniques. In this paper, we provided a review of the state-of-the-art methods based on deep learning, and a brief overview of traditional techniques. With the reported high performances, deep learning methods can be considered as the current state-of-the-art for glioma segmentation. In traditional automatic glioma segmentation methods, translating prior knowledge into probabilistic maps or selecting highly representative features for classifiers is challenging task. However, convolutional neural networks (CNN) have the advantage of automatically learning representative complex features for both healthy brain tissues and tumor tissues directly from the multi-modal MRI images. Future improvements and modifications in CNN architectures and addition of complementary information from other imaging modalities such as Positron Emission Tomography (PET), Magnetic Resonance Spectroscopy (MRS) and Diffusion Tensor Imaging (DTI) may improve the current methods, eventually leading to the development of clinically acceptable automatic glioma segmentation methods for better diagnosing

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