STUDY OF PATCHMATCH BASED TREE-SEED FUZZY CLUSTERING FOR ISCHEMIC STROKE LESION

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ABSTRACT

Ischemic Stroke Lesion (ISL) arises when the artery of the brain gets blocked. The blood provisions nutrients and oxygen to the brain and take out carbon dioxide and other waste cells. In case an artery gets congested, the brain cells will not be able to function and will ultimately stop functioning (Khoshnam SE et al 2017). Nerve symptoms and symptoms of IS usually occur abruptly but can also be sometimes progressive in nature. Signs and symptoms vary based on the position of the occlusion and the flow (Sommer CJ 2017). Atherosclerotic stroke is generally found in elders, and arises without symptoms in 80% of the cases. IS can be initiated by a variety of ailments, like contraction of the arteries head or neck region (Jiang X et al 2018).This is usually produced by atherosclerosis, deposition of cholesterol, or generation blood clots which arise as a consequence of rapid heartbeat, heart attack, damages in heart valve, or some other underlying origins, including drug overdose, severe blood vessel injury in the neck, or abnormal blood flow (Renna R et al 2014). MRI is extensively utilized to identify cerebral ischemia.

Keywords: Ischemic Stroke, Image Segmentation

PROBLEM DEFINITION

Annually, approximately 16,000 new cases of brain tumours are discovered in people all over the world, with over 60,000 people currently suffering from one. According to the NHS, the global incidence of brain tumours has greater than before, and it is now a major concern (brain Tumour studies 2019). Gliomas of the brain and critical fearful device account for up to 30% of all gliomas; roughly 80% of these are spiteful gliomas

(Goodenberger and Jenkins 2012). This discovery demonstrates the high cost of a well-planned tumour treatment. Given the wide variety of brain tumours that exist around the world, primary brain tumours are extremely rare. Tumors typically begin in the brain or a primary anxious device and only hardly ever spread to other parts of the corpse. Brain tumours that spread to other organs, such as the liver or lungs, are extremely uncommon. The vast majority of these tumours have spread (Paolillo and Schinelli 2015). As a result, depending on the histological appearance of the tumour, most initial brain tumours are classified as low-grade gliomas (LGG) or high-grade gliomas (HGG) (HGG).

Surgery, radiation therapy, and chemotherapy are all used in the treatment of gliomas by clinicians. Tumor treatment outcomes are influenced by the location, kind, and severity of the tumour. Because of this, tumour segmentation plays a crucial role in the development of surgical procedures and treatment plans. Clinical imaging modalities identify and assess tumours. To assist with surgery and radiotherapy planning, selecting the optimal treatment for a certain clinical diagnosis is necessary (Fink et al. 2015). While looking for the target volumes' contour on C-MRI (conventional magnetic resonance imaging), it can be useful for radiotherapy planning for high-grade gliomas (a type of brain cancer) (Niyazi et al. 2016). Through spatial information integrated throughout several go-sectional images, the MRI 3-d slice illustration decreases mistakes in medical practise while also assisting radiologist in seeing 3-dimensional anatomy from go-sectional photographs (Wu et al. 2010). Tumor assessment necessitates manually drawing a circle around the target area to capture the full 3-D quantity of the tumour. Although manual tumour margin segmentation Time-consuming Semi-automatic methods require less than 2 minutes each slice when used properly. Semi-automatic methods require less than 2 minutes each slice when used properly. minutes per tumour and can take up to sixteen minutes per tumour (Odland et al., 2015) Visible detection by humans elements in a photograph capabilities is also limited, increasing the likelihood of human error during guide segmentation. furthermore, This means that, for large MRI datasets, computerized segmentation will always be useful.

MACHINE LEARNING AND FEATURE EXTRACTION

When techniques were first developed, they comprised of three steps: pre-processing of magnetic resonance images (MR pictures), feature development, and extraction and classification. When pre-processing images, the median filter was employed for the purpose of improving the image quality while also maintaining the edges [37]. Image segmentation using clustering algorithms such as k-means, fuzzy C-means, and others results in the generation of helpful features from images. When it comes to understanding and interpreting photographs, image segmentation is critical. Tissue classification, tumour identification, tumour volume estimation, blood cell delineation, surgical planning and matching are just a few of the many uses in brain imaging that it has to offer. In [17], a brain tumour segmentation technique is applied to 3D MR images by means of a CNN. [33] proposes the use of a deep neural network to detect the anatomical structure of the brain automatically. Using a combination of discrete Gaussian and higher-order patterns such as Markov-Gibbs patterns, random field classification is utilised in a voting technique for an ensemble of visual appearances such as intensity and adaptive form modes, as well as in other applications. [32] describes the development of a cross shallow auto-encoder combined with a Bayesian fuzzy clustering-based segmentation technique. Following denoising with a non-local mean filter, a Bayesian fuzzy clustering strategy is used for the segmentation of brain tumours in this study. The approach is described in detail below. In [11], the 2D MRI images are partitioned into the left and right hemispheres, and statistical parameters such as mean, homogeneity, absolute value, and inertia are generated for the Support Vector Machine (SVM) classifier before being fed into the classifier. Because of the large amount of features in step two, most studies include an additional step to extract features that contain more significant information using methods such as principal component analysis (PCA), SIFT detectors, and SURF descriptors [18], which are described below. In [10], after performing a hybrid feature extraction using a covariance matrix, a regularised extreme learning approach is utilised to categorise brain abnormalities and determine its severity. The use of evolutionary algorithms such as particle swarm optimization (PSO) for selecting from a fusion of features is also discussed in [30]. On image analysis, classification methods such as k-nearest neighbours, decision trees, Support Vector Machine (SVM), the Naive Bayes, expectation-maximization, and the random forest are the most commonly used machine learning techniques [38]. Features are extracted for a hybrid Functional Near-Infrared Spectroscopy (fNIRS) and Electro Encephalo Graphy (EEG) brain-computer interface in [14] and categorised using SVM and Linear Discriminant Analysis (LDA) (LDA). Convolutional Neural Networks (CNN) are becoming increasingly used in various fields, including medical imaging, video analysis, and natural language processing, for feature extraction in a variety of applications. The capacity to recognise the most important patterns and information from the training images is the most important feature of CNN's performance. For example, VGGNet[31], GoogleNet [36], and AlexNet [19] are successful image classification architectures that have been widely employed in medical pictures, such as brain abnormality detection. It is discussed in [4] how to perform pre-processing and data preparation using 3D filters and CNNs with multi-path and cascade designs. In order to create a range of new portraits of a person with diverse expressions and poses, a pixel CNN architecture is used. In [39], a cascade of CNNs is used to iteratively generate a room decoration from the ground up. Because CNN has a significant computational cost, researchers are attempting to develop new, computationally simple models that are accurate in tumour classification while maintaining low computational costs. The use of an ensemble of tiny collaborative learners rather than a complicated network is a common strategy for meeting the needs of quick training execution and convergence, among other things. These peer networks' learning processes can be completely independent of one another or they can be completely dependent on one another. A common machine learning objective is to estimate the distribution of data, which is one of the most challenging problems to solve. For example, there are hard-coded relationships between image pixels and their neighbours, which are impossible to identify without prior knowledge of the relationship. In this case, the auto-regressive models are data-driven estimators that discover such connections in a large amount of data. The better images created by these models are conditioned on noisy or incomplete data, and this is the output of the models. An acceptable density estimator is likely to be used to tackle a wide range of classification, regression, missing data, and other problems of this nature.

REVIEW OF THE LITERATURE

INTRODUCTION

This chapter begins with a review of the relevant literature before moving on to look at various approaches to the problem at hand. This chapter focuses on the segmentation of brain tumours in MRI images. The previously proposed automatic methods for brain tumour segmentation in MRI images are reviewed and discussed in depth. Aside from that, it also discusses the protocols for evaluating the segmentation results and related work on the segmentation of ischemic stroke lesions used in this chapter.

A Gautam et al. 2019 segmented the ISL from the MR images by Random Forest method. It contains two steps: (i) image pre-processing, (ii) Feature extraction, and (ii) segmentation. For the pre-processing of images, wavelet transform is utilized that have the properties of signal decomposition, modelling, analyzing, and reconstruction. Here, the input signal is initially delivered through a Low Pass Filter (LPF) &a High Pass Filter (HPF). After pre-processing, the voxel intensities are extracted from various portions of the brain. Finally, segmentation is then performed by thresholding based on histogram and random forest classifier. The combination of two techniques gives higher accuracy for their system. The drawback in this method is that is that it fails to identify small lesions and therefore the dataset size should be increased.

A Subudhi et al. 2018 incorporated Darwinian particle swarm optimization (DPSO) Delaunay Triangulation (DT) to automatically segment the regions of stroke lesions. Their approach comprises of three phases: pre-processing, segmentation, and classification. At the initial phase, the images are de-noised by using Wiener Filter (WF) and the edges are sharpened by spatial 3×3 mask. At the second phase, non-overlap regions are obtained by applying DT, DPSO was applied to get the binary lesion, and then the unwanted artifacts are removed by morphology. At the final classification phase, the geometrical and statistical features are extracted by random forest algorithm. They validated the performance on 192 MRI images collected from various stroke subjects and concluded with better results. However, this approach failed to estimate the volume of the lesion.

V Rajinikanth et al. 2018 introduced a semi-automated technique for the segmentation for stroke lesions by combining Social Group Optimization (SGO) and Fuzzy-Tsallis Entropy (FTE). This framework can be segmented into two segments: pre-processing and post-processing. The images are preprocessed by employing SGO based on FTE. Here, FTE provides solution for multi-level thresholding problem which helps to enhance the image qualities than most of the other techniques. The evaluation conducted under ISLES 2015 dataset proved greater accuracy with better image statistical, quality, and similarity measure. However, the computational time and the error rates are high.

GB Praveen et al. 2018 used Stacked Sparse Auto Encoder (SSAE) for the segmentation of ISL. At the pre-processing stage, (i) the intensity is made constant throughout the image by field correction technique, (ii) unit variance and zero mean is obtained by patch normalization, (iii) redundancy in the pixel is removed by making the pixels of the adjacent layer less correlated. After, pre-processing, the patches are extracted from the testing and the training data. Then, the features are learned in an unsupervised fashion by auto encoders which comprises of three layers: input, hidden, and output layer. Here, the input is compacted into latent space and the output is reconstructed. This scheme has the benefit of compressing the data as well as reducing the dimensionality.

Z Liu et al. 2018introduced residual Fully Convolutional Network (Res-FCN). Here, the parameters are tuned by gradient based method so that the difference between the predicted and ground truth values are minimum. Initially, all the images are normalized to unit variance and zero mean. During the training process, the patches are extracted using a sliding window scheme. At the testing phase, the intensities of the images are normalized and the patches are extracted. For the extraction of features, they utilized ResNet structure comprising of bottleneck blocks and filters.

The Res-FCN incorporated sections: convolutional layer, bottleneck block, and loss function. The convolutional layer learns the features by stochastic gradient descent approach. The bottleneck block comprises of several convolutional layers to shrink the dimensionality of the features, to restore the depth, and to have the output same as the size of input. Finally, the loss function measures the error by dice coefficient. The advantage of this method is that it is sensitive to both small and large lesion. But, stroke classification is not so perfect.

A Subudhi et al. 2018 presented lesion segmentation based on watershed method. This system includes edge detection, filtering, feature extraction, and classification. Initially, the edges in the image detected using fuzzy system in which the RGB image is transmuted into grayscale image. The image is then filtered by gradient filter and the watershed algorithm separates the lesion from the background. Now, the geometrical and statistical features such as autocorrelation, variance, entropy, perimeter, eccentricity etc. are extracted and are given as the input to the random forest classifier. This system has less classification error, low computation time, and higher accuracy. However, this method fails to identify the existence of false positives.

PG Bharathi et al. 2019 detected ISL by combining random forest and k-means clustering. At the pre-processing stage, the intensities are made constant throughout the image by bias field correction scheme. The textural features like correlation, variance, entropy, homogeneity, cluster prominence etc. are then extracted by Gray Level Co-occurrence Matrix (GLCM). Due to the occurrence of huge quantity of unlabeled data, the features are learned by k-means clustering. Now, the dimensionality of the features are reduced by Principal Component Analysis (PCA) which discards the irrelevant features and keeps only the relevant features. At the final stage, the random forest scheme classifies the result.

ISCHEMIC STROKE LESION-RELATED WORKS

In the world, strokes are a major cause of death and incapacity (Subbanna et al. 2019). In an ischemic stroke, blood flow to the brain is restricted, resulting in localised necrosis of the affected areas. Due to the fact that the sore volume is an important endpoint for clinical preliminary studies, an extremely precise and reproducible programmed division is extremely valuable. This is a difficult task, however, due to factors such as the wide range of options that are all equally fit for purpose, location, and appearance. Abulnaga and Rubin then developed for the ISLES 2018 test a fully convolutional neural organisation model for dividing ischemic stroke sores in CT perfusion images (2018).

Chen et al. use a clever structure based on deep CNNs to fragment DWI's intense ischemic sores (2017). An enormous dataset of 741 subjects was used to validate their findings, which led to a mean precision of the Dice coefficient acquired, of 0.67, in the final analysis. Subjects with small and large sores had mean Dice scores of 0.61 and 0.83, respectively (Chen et al. 2017).

Also, Kamnitsas et al. (2017a) found that the difficult task of sub-intense stroke sore division using a double pathway that was 11 layers deep, using a 3D convolutional neural organisation called DeepMedic, was successfully completed with amazing execution. Using a more advanced thick net tight association design to improve the back spread of picture data and slopes, Zhang et al. (2018) developed the 3D FCDenseNet. They propose a different strategy for fragmenting sub-intense stroke sores unimodally from FLAIR MRI datasets in a concentrate by Subbanna et al. (2019). It makes use of three different sources of information to develop and evaluate a method for dividing injuries. To compare, two strategies that relied on convolutional neural organisations, as well as three stage level-sets that used multimodular imaging datasets, produced better results in the ISLES 2015 test.

DISCUSSION & OUTLOOK

Critical Review of the Current State of the Art

We reviewed the current state of medical image analysis for brain tumour studies in this review article. Tumor growth modelling was included in some of the registration methods in addition to segmentation and registration. The

Nearly two decades have passed since the first attempts in this field were made, but results are beginning to show that the methods have matured recently and are being used more frequently in It's normal to expect to see clinical practise. On multi-sequence data, most segmentation approaches use classification methods that use different features and take into account spatial information from a neighbourhood. On images from standard clinical acquisition protocols, the trend is not only to segment the tumour but also to delineate tumour subcompartments and different healthy regions. This gives the doctor more information on which to base a diagnosis, tumour monitoring, and therapy planning. In addition to assessing the accuracy and robustness, computation time is an important criterion. The current standard is for processing to take only a few minutes. Instead of selecting the technique first and then attempting to make it work on the current problem, a better problem-oriented segmentation technique selection could be made in the future by paying more attention to feature selection than the segmentation algorithm. There are two types of registration: intra-patient and inter-patient. Most tumour images require tumour image-specific extensions of standard registration algorithms in intra-patient registration because of tumour growth or resection effects. In most inter-patient registration approaches, tumor-bearing brain images are registered with a normal atlas. This is the most common approach. This can be used for statistical brain tumour atlases or for atlas-based segmentation. It's been suggested that one method of resolving this problem is to use registration methods alone; however, another approach involves using tumour growth modelling in conjunction with registration methods. However, the integrated approaches tend to be more accurate, while the registration approaches are more general. The tumorgrowth model, on the other hand, adds complexity and therefore, risks. The enormous computation time, particularly for integrated approaches, is a major issue. As a result, for the time being, these techniques should be viewed as purely experimental and will not see widespread clinical application until computational speed is improved. Traditional segmentation techniques are more adaptable and can handle multiple modalities at the same time than atlas-based segmentation methods, which rely on registration for segmentation. In addition, it is now possible to more easily treat specific tumour subcomponents. When segmenting tumor-associated tissues and structures, such as subcortical structures or functional areas, atlas-based methods have an advantage. Surgical or radiation treatment options may need to adjust as a result of this.

Many tumor-growth modelling approaches, however, have issues with multifocal lesions. We found that some papers in the literature lacked precision while researching for this article, describing what exactly was done, what type and grade of tumour was taken into account, what image data was used or how the algorithm performed in terms of robustness, accuracy and speed The many blank fields in the displayed tables are an easy way to see this. Medical image analysis for brain tumour studies, in particular, should pay more attention to differences based on tumour type and grade, as well as algorithm robustness.

CLINICAL REQUIREMENTS AND APPLICABILITY

Though much research has been done in this area in recent years, there is still a long way to go before it can be used clinically. Manual tumour delineations are still used by clinicians in many cases, despite the enormous amount of work and the lack of objectivity they entail. Researchers and clinicians aren't communicating well, which is causing this. It is difficult for clinicians to use many of the tools that have been developed thus far because they are purely research tools. As a result, future development efforts should focus on integrating the newly developed tools into more user-friendly settings. Real-time segmentation will be difficult to achieve, but computation times exceeding a few minutes are unacceptably long in clinical routine. This is an important consideration. Instead of focusing on feasibility studies that use only pure research data as image material, more researchers have recently tried to consider standard clinical acquisition protocols when developing their methods. This should help the app get out to more people faster. Robustness is a must for everyday usage. If a method consistently fails in some cases, doctors will lose faith in it and refuse to adopt a new approach. A major step for every new method should be demonstrating its robustness thoroughly. A complete standard for image acquisition protocols has yet to be established. Automatic methods for medical image analysis can only be used to the fullest extent if image data has been collected according to a well-defined protocol at multiple clinical locations. The standardisation of automatic methods is expected to have a significant impact on their applicability and spread, as it will eliminate the need for fine-tuning based on specific imaging characteristics. Traditional brain tumour treatment includes resection, followed by radiation therapy and chemotherapy using the drug temozolomide (TMZ) (186). The traditional Macdonald criteria (127) for tumour response evaluation are increasingly recognised as inadequate because of recent changes in glioma treatment. These criteria do not cover the effects of pseudo-progression and pseudo-response. There have been numerous novel MR-techniques developed since the early 1990s, now widely used in clinical practise, that allow non-invasive retrieval of tumour morphological, functional, and metabolic properties (e.g. diffusion-weighted imaging, dynamic susceptibility contrast enhanced perfusion imaging, and MR-spectroscopy (MRS)). Together with advancements in medical image analysis's ability to estimate tumour volume, these techniques may be able to fill the void left by the current lack of an integrated platform for advanced tumour assessment. Eventually, a dialogue should be started to persuade practitioners that, despite the fact that an automatic tool may be less accurate than the manual method in some cases, it offers greater objectivity, which is critical in longitudinal studies. Furthermore, certification is required before automated tumour image analysis methods can be used in routine diagnostics. Accordingly, commercial software packages won't be available before the app makes a breakthrough in the clinics.

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