Brain Tumor Segmentation with Parallel Implementation of Fuzzy C-Means using Multi-Core CPU

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***Abstract*** -**Magnetic Resonance Imaging (MRI) is extensively utilized in medical practice. Segmentation of the MRI brain image is important for the detection of anomalies in the brain. However, due to the symbiosis of intensity and noise, Magnetic Resonance Imageing has become a difficult task to divide the brain's image into distinct groups. Brain Tumor Division aims to differentiate tumor tissue from activated cells, necrotic cores and edema from white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). MRI-based brain tumor segmentation studies in recent years are gaining more attention due to the enhanced soft tissue contrast of non-invasive imaging and Magnetic Resonance Imaging (MRI) images. With nearly two decades of development, innovative approaches to use computer-aided techniques to the field of brain tumors are becoming more mature and approaching common clinical applications. In this paper, an enhanced observational fuzzy c-instrument (FCM) method based on similarity measurement is proposed to improve the segmentation performance of MRI brain images [1]. However, High computational requirements when working with big data sets are the principal problem with these algorithms. Nvidia's GPU today plays a major role in implementing such time-consuming algorithms to decrease the complexity of time [4]. For dissection of the tumor area, the mechanism of the sliding window is applied to the CPU (host), in which a 45x45 dimensional window is taken to classify whether the tumor area is present in the specific window. For optimal segmentation on the GPU (device), the fuzzy C means method is applied to obtain the exact location of the tumor. The algorithm implementation on the CPU achieved a speed of 17.6 for the BRATS data set [2].**

## INTRODUCTION

Medical imagery is now one of the most important scientific diagnostic and treatment approaches for human brain diseases over the last decades. Several diagnostic imaging systems, such as X-ray Computed Tomography (CT), Positron Emission Tomography (PET), Single-photon Computed Tomography ( SPECT), and Magnetic Resonance Imaging ( MRI), are constantly advancing and are widely used. Working as an advanced medical imaging tool, MRI is able to give non-invasive, detailed MRI of brain with high contrast and high spatial resolution between different soft tissues. MRI has gained widespread attention for these advantages and is widely used in clinical applications [3].

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Brain tumor, a collection of abstract cells in the brain. It destroys brain cells and increases softness in the brain. The general trend is that humans with brain tumors have seen tremendous rates in recent years, such as changing the lifestyle of mobile phones, frequent employment of virtual environments, and more. There are over 700,000+ people living with a major brain tumor in the US, and in 2017 there were more than 79,000 further diagnoses. Only four drugs are approved by FDA as a potential substitute to brain tumor cases and their shocking prognosis, and have been a method for brain tumor treatment over the past thirty years [4].

When analysing MRI of brain, an Precise division of the anatomical structure and determination of the exact volume of tissue can help identify and diagnose diseases such as Schizophrenia, Dementia, and multiple Sclerosis with morphological changes in brain tissue. However, MRI of brain are usually characterized by artefacts such as unknown acquisition noise, intensity asymmetry, and partially impact effects. These artefacts make the task of dividing MR brain images. Although manual separation of trained professionals is reliable, this process is time-consuming and there can be human mistakes. Therefore, there is a fierce competition for computer-aided segmentation which can achieve accurate and optimal results [3].

Precise automatic brain image segmentation of Magnetic Resonance (MR) images are a requirement for functional brain assessment of large-scale experiments of images collected at all ages. In particular, in the last 10 years, the study of neonatal brain image segmentation has expanded rapidly. In particular, over the past decade, the study of neonatal brain image segmentation has grown rapidly. One well known method for segmentation of MRI is the use of atlases, although pattern recognition techniques are sometimes used in conjunction with atlas-based approaches. To get an anatomically accurate segmentation, these techniques involve precise spatial and intensity detail. Spatial detail is given as an atlas for atlas-based approaches, which is skewed to correspond with the image at hand. The function is defined by spatial data such as proximity to the space of the atlas, proximity to the brain mask, likelihood of an earlier segmentation step, or implementation of physical constraints for pattern recognition techniques. Intensity information, pattern recognition methods are implemented into a set of intensity-based features, and atlas-based techniques are normally done by comparing intensity values between atlases and target images [10].

There are 2 types of brain tumours: Benign and Malignant. In fact, the most-used grading scheme has been released by World Health Organisation. It classifies brain tumors under the microscope, from Grade I - IV. Generally, Benign brain tumors Grade I and Grade II (low grade); malignant brain tumors Grade II and Grade IV (high grade). Low-grade tumors are generally left untreated which can worsen high-grade tumors [15]. Tumors of the brain endanger the lives of people, and need early diagnosis and treatment. In the therapeutic context, brain tumor management choices include surgery, radiation therapy and/or chemotherapy.

Imaging techniques play a vital part in assessing patients with brain tumors as diagnostic imaging advances, and have a major effect on patient care. Recently, new imaging techniques such as Ultrasonography, Computed Tomography (CT), X-ray, Magneto Encephalo Graphy (MEG), Single-Photon Emission Computed Tomography, Electro Encephalography ( EEG), Positron Emission Tomography (PET), Spectral and Magnetic Resonance Imaging (MRI) have shown not only accurate and full aspects of brain tumors but also improved therapeutic targets in recent years. Improving the Sector Clinical Doctors to Study the Brain Tumor Mechanism. Clinical clinicians play an important role in the assessment and treatment of brain tumors. When clinically diagnosed with the brain tumor, radiological tests are performed to identify the location, size and underlying structure of the tumor. This knowledge is crucial to distinguish between various methods of treatment, such as surgery, radiation and chemotherapy. Therefore, detection of brain tumors with imaging techniques is now one of the big concerns in the radiology disciplines [15].

These sequence images include T1 weighted MR (T1w), T1 weighted MR (T1wc) with contrast enhancement, T2-weighted MRI (T2w), Proton Density-weighted MRI (PDw), fluid recurrence replacement recovery (FLAIR), and so on. Included. Figure 1 shows the axial portion of four standard series for glioblastoma (a type of brain tumor).

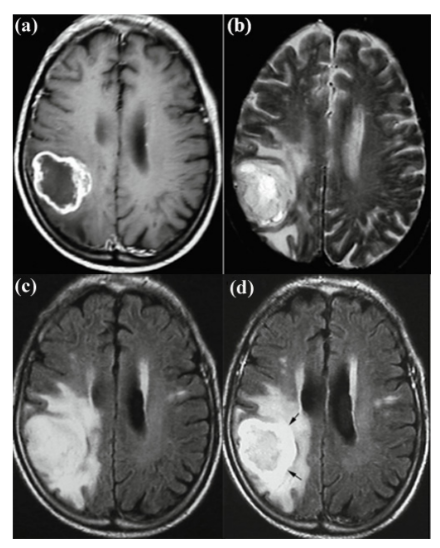


Figure. 1 (a) T1 Weighted MR (b) T2 Weighted MR (c) FLAIR (d) FLAIR with contrast enhancement [15]

Several methods have been proposed, such as atlas-based techniques, learning-based methods, active form-based methods, statistical parametric mapping (SPM) based on classical voxel, FMRIB automated segmentation tools (FAST) for segmentation of MR brain images. Method. And fuzzy clustering-based techniques. Fuzzy clustering-based methods are widely studied along with these techniques and used in the brain images section of MR. On the one hand, tissue distribution in MRI of brain is generally overlapping and complex, meaning that the information has a fuzzy property. It is appropriate to use clustering techniques. On the other hand, fuzzy-clustering enables a pixel to have more than one group (or classes) with different members. Such soft separation has advantages over other techniques when processing MRI of brain, because due to the partial volume effect the pixel intensity in MRI of brain may be a complex of multiple tissues. Hence this paper focuses mainly on methods of clustering-based segmentation based on Fuzzy C-Means (FCM) [3].

Tumor segmentation is generally the process of dividing an image into its constituent areas. However, there is much literature available for brain tumor differentiation. However, separation is still challenging at the right time for optimal treatment planning. The paper presents a great approach for brain tumor dissection, in which the window size is 45 X 45, which measures the overall tumor and measures the different characteristics. Further classification is done to check if the tumor is present in any instance. Additionally, parallel fuzzy c -means clustering is used for precise tumor separation from the obtained image, which is used in CUDA detector computing [4].

Nvidia's GPU (Graphics Processing Unit) has a vital role to play in reducing time complexity of the algorithm. Further, In the year 2006, NVIDIA briefed its own mainly parallel-programming model called as computed unified device architecture. It is a parallel programming model. This architecture utilises the most parallel computing engine from the GPU to solve different problems of reference computation. Additionally, it is an open source software, and is the original C language extension. There are two steps to any CUDA program, namely the host (Central Processing Unit), device (Graphical Processing Unit), or both, the CPU as well as the GPU. Equality of data in host code is not possible. Steps to display data equivalence are counted in device (GPU) code. The NVIDIA C compiler is used for CUDA programs which discriminate during the compilation process in two steps [4].

## Literature Survey of Some Related Works

The current section highlights some research work that improved the popular FCM algorithm's segmentation output. This also briefly highlights several methods for enhancing the time complexity of the algorithm for processing the image that were carried out by previous researchers.

Yuxuan Zhang et. al. [1] proposed PFCM method-based similarity measurement with local label data for brain tumor segmentation of the MRI. This method is depending on PFCM, which can detect outliers in the image. Defining similarity measurements based on similarity of the intraclass and similarity of the interclass, the proposed method can group linear and nonlinear data types. The method proposed may also solve the issue of cluster size sensitivity. In addition, the proposed approach uses local label information to retain more clarity of the image and to reduce the noise effect.

Yuxuan Zhang et. al. [3] proposed a Non-intuitive method of clustering FCM, namely ICFFCM for segmentation of the MRFF images. ICFFCM does not have cluster centres. The clustering is accomplished by adding the proposed similarity of pixel-to-pixel and the similarity of pixel-to-cluster. The resemblance of pixels to pixels takes into account spatial data and intensity values which reduce the influence of disturbance on MRI of brain.

Wahengbam Kanan Kumar et. al. [5] proposed a novel FCM clustering technique to improve contrast enhancement and separate the 3 main human-White Matter, Grey Matter and CSF underlying areas. The proposed technique-'FAAGKFCM' introduces a new objective method, which replaces the usual Euclidean distance metric with the GRBF kernel to use a new WG image.

Xiaohong Jia et. al. [7] proposed super pixel based fast FCM clustering algorithm (SFFCM) for segmentation of the image colour. The proposed SFFCM is more advanced than state-of-the-art clustering technique, as it delivers the precise segmentation results and requires the short period runtime.

R. Meena Prakash et. al. [9] proposed Fuzzy-C For the segmentation of Synthetic Aperture Radar image, means non-local spatial data. Fuzzy Means Splitting is noise sensitive. Therefore, Due to the nature of spatial distortion in the partitioning of Synthetic Aperture Radar images the accuracy of the separation is low. Non-native spatial information for overcoming the FCM disadvantage is included in the partition. The approach proposed is tested on Synthetic Aperture Radar images and has a performance gain of 6 per cent relative to current techniques.

Max A. Viergever et. al. [10] proposed a CNN technique for segmentation and classification of MRI of brain shows accurate segmentation results in images taken at different ages and with different protocols.

N. Santhiyakumari et. al. [11] proposed a program that evaluated the effectiveness of FCM and k-Means, with controlled initialization of histograms. Fuzzy C Means can detect both tissue classes and backgrounds. It merges Grey Matter, Ceribrospinal fluid, and necrotic focus into one category, and WM and peripheral edema into another category. FCM produced three empty groups in the first two test images and three empty groups in the last two. k -means can detect Ceribrospinal fluid, White Matter, Grey Matter, Edema, necrosis, and background area. But, parts of White Matter are grouped with growing Edema, and vice versa. This cross talk happens between Ceribrospinal fluid, necrosis and Grey Matter. It occurs when the severity symptoms of Edema and the components of White Matter are completely equal. Similarly, Ceribrospinal fluid, Grey Matter, and necrosis components also share homogeneous severity features. GBM's fully automatic partitioning is complex, and the intensity-dependent partitioning of GBM-Edema complex MRI is not possible.

Yanning Zhang et. al. [13] In this paper, A very fast and robust FRFCM image segmentation technique is proposed to increase the performance and segmentation quality and minimize the impact of image noise. With the introduction of morphological reconstruction, local spatial data of the images was used to enhance the dividing effect. Since magnetic resonance is capable of reducing noise while maintaining object appearance, the trade-off between noise reduction and defence against diffusion is easily accomplished. Additionally, MR can provide good reconstructed results for a variety of images contaminated with noise.

Yanning Zhang et.al. [14] proposed a new method for segmentation of images by mixing the Fuzzy C Means clustering algorithm with a rough-set theory. First, the value table of the attributes is built on the basis of the FCM partitioning results with different clustering numbers, and the images are divided into number of smaller regions based on the attribute values’ integral relation. Then, by subtracting the value the weight values of each attributes are obtained and used as the basis for calculating the difference between regions, and then the similarity of each region is estimated by the similarity relationship defined by the region of difference. Lastly, the final analogous relationship described by equality is used to combine regions and complete the segmentation of images.

Jianxin Wang et. al. [15] In this paper a detailed review of cutting-edge brain tumor resection techniques based on MRI is given. Present brain tumor resection procedures execute MRI due to the isolation of non-invasive and fine soft tissue from the MRI, and use grouping and clustering techniques with specific features and consideration of local spatial details. These methods are intended to give the doctor a tentative test, tumor tracking and surgical preparation recommendation.

Haifeng Yao et. al. [2] proposed a brand-New parallel implementation approach for batching small computing tasks using CUDA in GPU is proposed.

Suraj Shama et.al. [4] Exact brain tumor segmentation is one of the essential tasks in the production and analysis of medical images as it deals with segmenting tumor region data from brain MRI sequences. In this paper, a significant technique of segmentation of brain tumors from the FLAIR MRI sequences is by classifying the local window followed by clustering of parallel fuzzy c means. Parallel bias field correction implementation FCM Image Segmentation algorithm. Improved Edge Detection algorithm for segmentation of brain tumors. In CUDA environment, GPU built image segmentation using first-order edge detection operators.

Neeraj Sharma et.al. [12] This paper describes the type of performance gain in implementing the basic and essential image processing technique which is achieved by converting the serial programming model, the first-order edge detector operator, to the parallel programming model. The image processing algorithms technique is a kind of algorithm that works substantially in achieving the best pay for CUDA. In general, image processing algorithms mean that one type of computation, as we have seen in edge detection, is often heavily repetitive. Most of those methods are processed into one another individually.

## BACKGROUND WORKS

Segmentation methods for brain tumors, focusing on various principles, can now be divided into different categories. In the clinic, brain tumor segmentation techniques are typically divided into three main groups, including manual, semi-automatic, and fully automated segmentations, based on the types of human interaction required.

For manual brain tumor resection, brain tumor experts need to study the details given in brain tumor imagery and some basic expertise such as anatomy, as manual brain tumor dissection is meant to draw borders and anatomy for human brain tumors. Describing the area with several labels. To date, manual segmentation has been widely applied for clinical testing. In the clinic, as multiple images of brain tumors are emerging, manual dissection of different areas of brain tumors can become an error-prone and time-

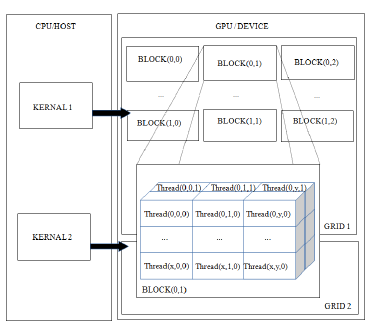


Figure. 2a Model of Programming GPU-CUDA Model [4]

consuming task for professionals and in a way, can lead to poor outcomes. Therefore, more sophisticated partitioning techniques such as semi-automatic and fully automated partitioning techniques are needed to solve this problem. It includes patient, interaction and computational applications primarily for semi-automated brain tumor segmentation. The user will input those parameters in semi-automated brain tumor methods, and is responsible for analyzing visual information and providing machine computing feedback. Software computing is designed to produce algorithms for the segmentation of brain tumors. Partitioning involves user- and software computing information and interactions. The semi-automated approaches of segmentation of brain tumors are categorized into three major processes: initiation, response regression, and evaluation. Although Brain Tumor Semi-Automatic Segmentation Methods can improve results than manual segmentation, it can yield different results at different times from different experts or from the same user. Therefore, fully automated brain tumor segmentation methods have been proposed.

The computer decides the classification of brain tumors without human intervention for a fully-automatic segmentation of the brain tumors. A fully-automated segmentation algorithm typically blends AI with prior knowledge. With the development of machine learning methods that can simulate human intelligence for effective learning, a completely automated study of brain tumor segmentation has become a main research question. Semi-automatic and fully automated tumor brain image segmentation poses significant obstacles, usually with partial volume effects for images of brain tumors with discontinuous and irregular boundaries. This paper divides current MRI-based brain tumor differentiation methods into three main categories: conventional methods, classification and clustering techniques, and slick sampling methods [15].

1. FCM Method

Dunn first implemented the FCM approach and Bezdek later expanded it. FCM solves the problem of clustering N

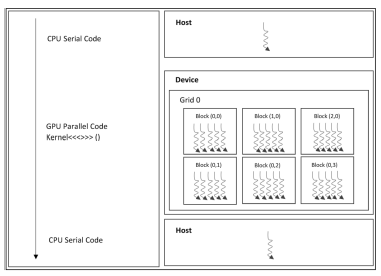


Figure. 2b Work flow of CUDA [4]

calculated data points or objects in a cluster of C’s through a process of recursive minimisation. The purpose of Fuzzy C Means is defined as function

(1)

Where n represents the total pixels, c is the number of clusters, m is the fuzzy factor and is normally set to 2, xk is the kth of data point or object evaluated and vi is the prototype of the ith cluster. Minimizing objective function jm with the following modified equations can be obtained through an iterative process:

(2)

(3)

In an analysis of brain tumor resection, brain tumors were classified into groups of tissue, including unsaturated cells, necrotic cores, and edema. Using this algorithm, segmentation images can be generated which show clinically important neuroanatomic and neuropathological tissue contrast information from raw MR image data. Some researchers subsequently integrate additional information into the feature vectors which cluster using FCM. MR images are processed using a method that combines knowledge-based techniques with multispectral histogram analysis to deal with brain tumor differentiation. A knowledge-based fuzzy clustering approach was proposed, and 3-D components attached to form the tumor structure were added to section MRI images of brain tumors. A new technique of image segmentation called Fuzzy Knowledge-Seed Growing Region (FKSRG) has been proposed based on fuzzy knowledge and improved seed area [1].

### GPU and CUDA

Individual Blocks, Grids, and Threads form the CUDA design as shown in Figure 2 CUDA may complete a large number of parallel threads. Threads are grouped into blocks and block groups are termed grids. Implementation requires flexibility within the same types of organizations in constructing the specific levels of hierarchy. The grid is the

|  |  |  |
| --- | --- | --- |
| Figure 3a. Design implementation using Single-core CPU | Figure 3b. Design implementation using Multi-core CPU | Figure 3c. Design implementation using GPU |

position of the thread blocks, which will be executed separately.

Blocks are also arranged into 3-dimensional arrays and each block has its own specific block ID (blockIdx). The kernel function runs the threads, and each thread has a unique Thread ID (Thread IDX). GPU threads don't strictly restrict the total size of a single block.

In addition, the CUDA workflow is shown in Figure 3 Basically, the kernel refers to the code to be run on the GPU. The exact arguments have to be sent when running the kernel from host to device.

## IMPLEMENTATION

The block diagram of the system is given in Figure 3.

Basically, the entire implementation can be classified in to three steps image pre-processing, brain tumor segmentation in CPU and GPU and morphological operation.

### Image preprocessing

Prior to the advent of brain tumor dissection methods, Magnetic Resonance preprocessing operations were conducted because they are closely related to the features of the segmentation result. In general, to achieve the segmentation targets, raw MR images need to be prepared prier. These pre-processing activities include removing noise, skull-stripping, normalizing intensity, etc, and have a straight effect on the effects of differentiation of brain tumors.

The standard preprocessing function for image de-noise MRI. The noise in the MRI image makes it difficult to accurately delineate areas of interest between brain tumors and normal tissue. For this reason, it is necessary to pre-process the MR image to reduce noise and increase the difference between regions [15].

### Brain tumor segmentation

In the implementation we tried to significantly decrease the latency of data transfer from CPU to GPU, and vice versa. It is the serious problem of the time consumption of data transfer at the time of implementation. The hybrid implementation of Fuzzy C Means will be discussed here, which not only exploits a shared data object memory, but will also consider constant centroid memory in addition to registers. For cluster upgrade and terminating requirements, the portion running on host is the division operation. These two operations are preferable to perform on host because they do not both require processing power [4].

Basically, the entire implementation may be split up into two phases. One process is running on Host (CPU) and another is running on system (GPU). Host side is responsible for the operation of input and output, and device side segmentation of the brain tumor processes. Segmentation is done on single-core and Multi-core CPU and on GPU and time taken for segmentation will be compared. The time comparison for different CPU threads and different number of images is given in the table 1 and table 2 respectively.

|  |  |
| --- | --- |
| No. of Threads | Time (secs) |
| 1 | 227 |
| 2 | 143 |
| 3 | 112 |
| 4 | 95 |
| 6 | 95 |
| 8 | 95 |
| 10 | 95 |

Table 1. Time taken with different number of threads

### Morphological operation

After the segmented image is produced by the fuzzy c means algorithm, the resulting image may contain imperfection. The objective of using morphological operations is to remove the imperfections in the structure of image. The Erosion technique is used to overcome the imperfection in the image.

Table 2. shows as the number of images increases time taken by single-core CPU and multi-core CPU increases drastically.

|  |  |  |
| --- | --- | --- |
| No. of images | Single-core Processing (secs) | Multi-core Processing  (secs) |
| 1 | 8 | 11 |
| 2 | 19 | 15 |
| 4 | 40 | 21 |
| 10 | 90 | 40 |
| 20 | 185 | 78 |
| 50 | 480 | 193 |
| 100 | 970 | 389 |
| 150 | 1332 | 561 |
| 250 | 2488 | 956 |

Table 2. Time taken by Single-core and Multi-core CPU for different no. of images



Figure 4a. Input MR Image before segmentation

## EXPERIMENTAL SETUP AND RESULTS

1. *System Configuration*

Processor: Intel Core i3-5005U CPU @2.00GHz Dual core RAM 8 GB

Hard Disk: 1TB

GPU: Nvidia GeForce GTX 960

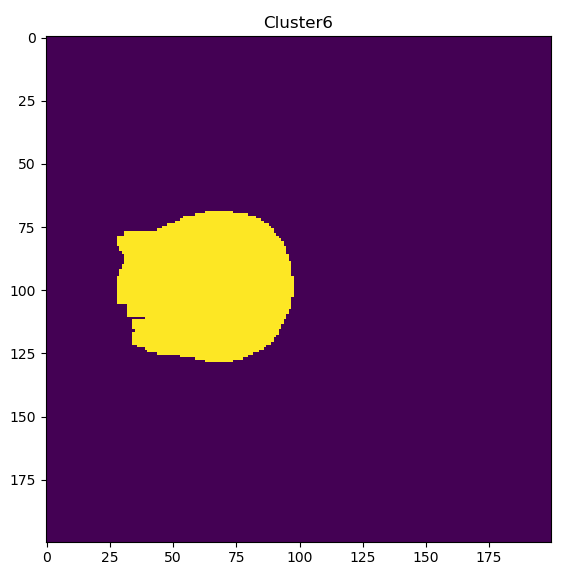


Figure 4b. Output of segemted image

1. *Brain Tumor Segmentation*

Figure 4(a) show the input image containing unhealthy tissues which will be sent into the fuzzy c means clustering algorithm after preprocessing. The Figure 4(b) shows the output produced after the morphological operation. Detailed explanation of Morphological operation is given in section IV.

## CONCLUSION

Till now, there are several brain tumor segmentation techniques available, such as improved edge detection, super-pixel based ERT, Fuzzy C Means, CNN based segmentation and many more. Implementation speed of Fuzzy c means clustering on multiple CPU cores is also important. This built-in automated tool is able to identify tumor-induced MRI and then tumor region segmentation. The remarkable accuracy of the proposed method in performance tumor segmentation due to its low time computational complexity shows our proposed system's efficiency. All the cores with structured threads are effectively utilized. Experiment shows that this system delivers exceptionally better results when compared with the methods recently proposed. For future viewpoint we can execute computation task of clustering in GPU using CUDA cores.

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