

# Automated detection and segmentation of brain tumors using CSS algorithm techniques

Dr. P. Dubois<sup>1</sup>, Dr. C. Martin<sup>1\*</sup>

<sup>1</sup> Faculty of Medicine and Biomedical Sciences, Université de Lyon, Lyon, France

## ABSTRACT

In medical image processing, Brain Tumor segmentation plays a vital role to segment an image more accurately and precisely. Segmentation is the process used to accomplish the tasks by dividing an image into meaningful parts which share similar properties. Magnetic Resonance Imaging (MRI) is a primary diagnostic technique for image segmentation. It is challenging task due to poor contrast and artifact which results in missing or diffuse organ/tissue boundaries. This paper describes the curvature scale space algorithm for segmentation. It involves Pre- processing, Segmentation using Curvature Scale Space (CSS), Feature Extraction and Classification using ANN. The artificial neural network is used to train and classify the stages of Brain tumor as benign, malignant or normal.

**Keywords:** MRI, curvature scale space, ANN

## INTRODUCTION

Brain is a complicated organ since it contains in excess of 10 billion operating synapses. The damaged brain cells are diagnosed them by splitting to make more cells. This regeneration takes place in a controlled manner. If regeneration of the cells gets out of control, the cells will continue to divide developing a lump which is called Tumor. Brain Tumor is a life threatening disease .The two major classification of tumor are Benign Tumor and Malignant Tumor. Benign Tumor is a non-cancerous cell. It does not cause death or serious injury. Moles are the example of benign tumor. Malignant Tumor is a cancerous cell. This malignant tumor tends to grow and spread in a rapid and uncontrolled way that can cause death and the Tumor are graded according to how aggressive. They are as A. Low Grade Tumor (Benign stage) B. High Grade Tumor (Malignant stage. There are different type of brain tumor they are i) Gliomas, ii) Medulloblastoma, iii) Lymphoma, iv) Meningioma, v) Craniopharyngioma, vi) Pituitary adenoma.

## LITERATURE REVIEW

Twenty progressive tumor segmentation algorithms were applied to a group of sixty five multi- contrast adult male scans of low- and best glioma patients - manually annotated by up to four raters - and to sixty five comparable scans generated using tumor image simulation software.[1] Quantitative evaluations unconcealed appreciable disagreement between the human raters in segmenting numerous growth sub-regions, illustrating the issue of this task. They found that totally different algorithms worked best for various sub- regions, however that no single algorithmic program hierarchical within the high for all sub-regions at the same time. Fusing many sensible algorithms employing a hierarchic majority vote yielded segmentations that systematically graded in particular individual algorithms, indicating remaining opportunities for more method enhancements. Cardiovascular magnetic resonance (CMR) has become a key imaging modality in clinical medicine follow because of its distinctive capabilities for non-invasive imaging of the internal organ chambers and nice vessels. A good vary of CMR sequences

are developed to assess numerous aspects of internal organ structure and performance, and important advances have jointly been created in terms of imaging quality and acquisition times. Plenty of analysis has been dedicated to the event of world and regional quantitative CMR indices that facilitate the excellence between health and pathology[2]. The goal of this paper is known about the structural and purposeful CMR indices that are planned to date for clinical assessment of the internal organ chambers. They embrace indices definitions, the necessities for the calculations, ideal applications in cardiovascular diseases,[7] and therefore the corresponding traditional ranges. Moreover, they review the foremost recent state-of-the art techniques for the automated segmentation of the internal organ boundaries that are necessary for the calculation of the CMR indices.

The segmentation of infant brain MR image into nervous tissue (WM), grey matter (GM), and cerebrospinal fluid (CSF), is difficult because of the low abstraction resolution, severe partial volume impact, high image noise, and dynamic myelination and maturation processes. Atlas-based strategies are wide used for guiding infant brain segmentation.[5] Existing brain atlases were typically made by equally averaging all the aligned example pictures from a population. However, such population-based atlases may not be representative of a testing subject within the regions with high inter-subject variability and therefore typically result in an occasional capability in guiding segmentation in those regions[3]. In this paper, they propose a completely unique patch-driven level set methodology for the segmentation of infant brain MR pictures by taking advantage of distributed illustration techniques. Specifically, they initial build a subject- specific atlas from a library of aligned, manually segmental pictures by

mistreatment thin illustration in a very patch- primarily based fashion. Then, the abstraction consistency within the likelihood maps from the subject-specific atlas is more enforced by considering the similarities of a patch with its neighboring patches. Finally, the likelihood maps are integrated into a coupled level set framework for a lot of correct segmentation. The projected technique has been extensively evaluated on twenty training subject's exploitation leave-one-out cross validation, and additionally on 132 extra testing subjects.

A new hybrid diffusion based level set technique is projected to with efficiency address the complicated image segmentation drawback totally different from the standard strategies; the planned technique is performed on image diffusion area instead of intensity area.

Firstly, the nonlinear diffusion supported total variation flow and additive operator rendering theme is performed on the first intensity image to get the subtle image. Then, the native diffusion energy term is built by playing homomorphism unsharp masking operation on subtle image therefore on implement an area piecewise constant search. To avoid trapping into native minimum created by native energy, international diffusion energy term is created by approximating subtle image in an exceedingly global piecewise constant method.

Besides, the regularization energy term is enclosed to possess penalization result on evolving contour length and maintenance of level set operate being signed distance function [4]. By minimizing the general energy purposeful that may be a linear combination of native energy, international energy and regularization energy, the evolving contour will be driven to approach the thing boundary.

Segmentation of baby brain MR pictures is

difficult because of scarce image quality, severe partial volume result, and in progress maturation and myelination processes. In the 1st year of life, the image distinction between white and grey matters of the baby brain undergoes dramatic changes. In particular, the image contrast is inverted around 6-8 months of age, and the white and gray matter tissues are intense in both T1- and T2-weighted MR images and therefore exhibit the extraordinarily low tissue distinction that poses important challenges for automatic segmentation. Most previous studies used multi-atlas label fusion strategy that has the limitation of equally treating the various available image modalities and is usually computationally high. To cope with these limitations, they propose a novel learning-based multi-source integration framework for segmentation of infant brain images.[9] Specifically, they use the random forest technique to effectively integrate options from multi-source pictures along for tissue segmentation. Here, the multi-source images include initially only the multi-modality (T1, T2 and FA) images and later also the iteratively estimated and refined tissue probability maps of gray matter, white matter, and cerebrospinal fluid.

**DRAWBACKS OF EXISTING**

**SYSTEM**

The major disadvantage of the present system, once Brain Imaging is finished, arrangement might occur typically throughout locating the portion, because the image is revolved to a hundred thirty degree. Current clinical ways that are accustomed differentiate the tumor from traditional tissues, even when the injection of a contrast medium, might not observe the tumor in boundaries of the MRI brain image. The planned system overcomes such location of arrangement throughout rotation.

Some analysis shows that folks littered with neoplasm died because of their inaccurate detection. Computed tomography (CT), magnetic resonance Imaging (MRI), positron Emission imaging (PET), Single positron Emission CAT (SPECT) are a number of the imaging technique used majorly to spot diseases. Mistreatment these scanners doctors are able to simply visualize and find the actual portion or space wherever the malady is being affected and at last to sight them. MRI could be a diagnosis tool for detection of tumor in brain and it offers bodily structure of brain. MRI uses force field to capture image of brain rather than X-Rays.

**PROPOSED SYSTEM**

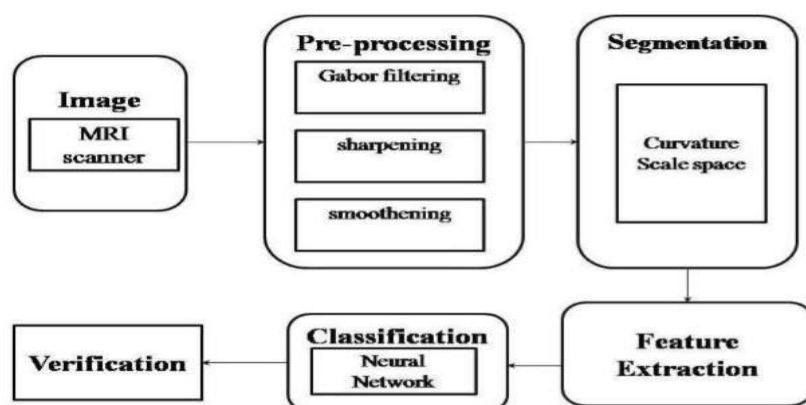


Fig. 1: Block Diagram of Proposed Method.

**Pre-Processing**

Mostly medical images appear to be inhomogeneous and poor contrast, hence it

require pre-processing for image enhancement so as to get most accurate and precise segmentation. The main aim of

the pre-processing is to improve the quality of images and to make it ready for further processing, thereby removing or reducing the unrelated and surplus parts in the background of the input images. Pre-processing is essential to be done to improve the quality for processing the image so as to get accurate output. By pre-processing noise and high frequency components can be removed by filters. In this proposed method we are using high pass and low pass filter for pre-processing. The high pass filter is used for removing a little quantity of low frequency noise from an N dimensional signal. The cutoff frequency of the filter used is fixed at 0.1. The median filtering is used to remove the high frequency components in MR images. The median filter is the most used method to reduce noise and improve image quality as it preserves the edges of the input image. The median is calculated by initial sorting the entire picture element worth from the encircling neighborhood in numerical order and then changing the picture element being thought of with the center picture element value. A  $3 \times 3$  square matrix neighborhood is used here. The linear transformation method is applied to the processed image in order to enhance image contrast. Gabor filters wants some forms of pictures because the input.[6]

These pictures need the method of computer algorithms as per the input image. These computer algorithms yield 2 kinds of pictures from computer Algorithm: wheezy image and magnitude image. The magnitude image is comparison with the wheezy image, which supplies the benefits of Dennis Gabor filters in numerous parameters.

### Segmentation

The Segmentation of a picture entails the division or separation of the image into regions of comparable attribute. The most objective of image segmentation is to extract numerous features of image which may be unified or split so as to make

object of interest on that analysis and interpretation are often performed. It includes cluster, thresholding etc. EM formula is most generally used for the reconstruction of the input image, whereas the extent set technique could be a numerical tool that facilitates to urge correct boundary values thereby serving to urge correct segmentation of the input image.

### CURVATURE SCALE SPACE ALGORITHM

CSS is one in the entire popular international and contour primarily based form descriptor technique that constructs a CSS image supported the input image contour. CSS image may be a cluster of multi-scale illustration of contours of the image that consists of shallow and deep concavities. It consists of many arch form contours, every associated with a concavity or a convexity of the curve. The most advantage of this methodology over the others is that it's sturdy with regard to noise, scale and alters in orientation. Moreover, each feature extraction and form matching are disbursed quickly. Therefore it's employed in visual perception, content primarily based image retrieval (CBIR), form similarity retrieval and leaf classification.

### Steps Involved in CSS

- The contour of the image is obtained mistreatment the canny edge detector.
- The contour of the image is then convolved with the mathematician kernel.

This method is named as smoothing of the image curve.

- The convolution includes 2 parameters like „u“ is termed arc length parameter and „ $\sigma$ “ is thought as parameter.
- The scale parameter „ $\sigma$ “ is step by step hyperbolic throughout convolution and therefore the get smoothed as „ $\sigma$ “.
- When „ $\sigma$ “ = zero, the smoothed

image is same as original image and because the  $\sigma$  will increase smoothed pictures gets blurred.

- The final CSS images include several arch formed contours that depend on the concavity (shape or inflections) of the object.
- The evolution of the curve (smoothing) stops once the quantity of curvature zero crossings become zero.

### FEATURE EXTRACTION AND SELECTION

Feature extraction could be a technique of capturing visual content of pictures for categorization and retrieval. Feature extraction is employed to denote a chunk of data that has relevancy for finding the process task associated with a precise application. Remodeling the input file from the info into a collection of options is termed options extraction of a picture. If the options extracted are rigorously chosen it's expected that the options set can extract the relevant data from the input file so as to perform the specified task.

### CLASSIFICATION[8,10,11]

The ANN segmentation algorithmic program may be summarized within the following steps:

1. Initialize the input of neurons to random values.
2. Apply the input-output relation to get the new output worth for every nerve cell, establishing the assignment of element to categories.
3. Calculate the center of mass for every category as follow:

$$\bar{X}_L = \frac{[\sum_{k=1}^n X_K V_{kl}]}{n_1}$$

Where is the range of pixels in class.

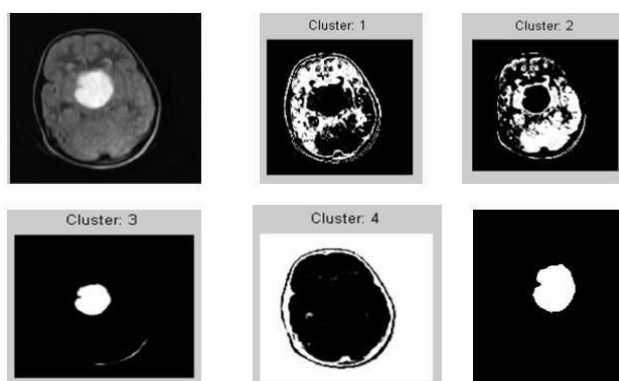
1. Solve the set of equation in (3) to update the input of every neuron:

$$U_{kl}(t + 1) = U_{kl}(t) + \frac{dU_{kl}}{dt}$$

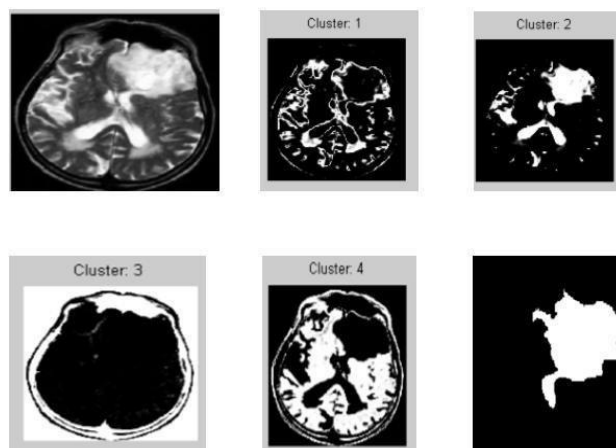
2. Repeat from step two till convergence then terminate.

### RESULTS

This paper uses BraTs dataset 2017 for detection of brain tumor and segments the tumor using CSS Algorithm. We examined pre- processing analysis for brain tumor detection using Gabor filter, the segmentation is followed by CSS algorithm. Feature extraction is done using GLCM, (Gray level Co-occurrence Matrix). Nearly 12 features are extracted and finally it is classified using ANN (Artificial Neural Networks).



**Fig. 2:** MRI Image with Benign Tumor. (a) MRI Image, (b),(c),(d),(e) Clustering of an Image (f) Segmented Image



**Fig. 3:** MRI Image with Malignant Tumor. (a) MRI Image (b),(c),(d),(e) Clustering of an Image (f) Segmented Image

## CONCLUSION

The projected CSS algorithm segments and classifies the tomography tumor pictures accurately. The process is initialized with preprocessing step. Noise in a picture is removed and quality of a picture is improved exploitation wiener filter with success. Then it's followed by segmentation and have extraction method with the assistance of Curvature Scale space algorithm. Tumor is curable if it's caught at earlier stages. This allows the doctor to know the precise progression of the illness state, which might facilitate to create a choice concerning the acceptable treatment, surgery and followed up by a series of illness control measures.

## REFERENCES

1. Menze, B. H., Jakab, A., Bauer, S., Kalpathy-Cramer, J., Farahani, K., Kirby, J., & Lanczi, L. (2014). The multimodal brain tumor image segmentation benchmark (BRATS). *IEEE transactions on medical imaging*, 34(10), 1993-2024.
2. Peng, P., Lekadir, K., Gooya, A., Shao, L., Petersen, S. E., & Frangi, A. F. (2016). A review of heart chamber segmentation for structural and functional analysis using cardiac magnetic resonance imaging. *Magnetic Resonance Materials in Physics, Biology and Medicine*, 29(2), 155-195.
3. Wang, L., Shi, F., Li, G., Gao, Y., Lin, W., Gilmore, J. H., & Shen, D. (2014). Segmentation of neonatal brain MR images using patch-driven level sets. *NeuroImage*, 84, 141-158.
4. Wang, X. F., Min, H., Zou, L., & Zhang, Y. G. (2015). A novel level set method for image segmentation by incorporating local statistical analysis and global similarity measurement. *Pattern Recognition*, 48(1), 189-204.
5. Wang, L., Gao, Y., Shi, F., Li, G., Gilmore, J. H., Lin, W., & Shen, D. (2015). LINKS: Learning-based multi-source Integration framework for Segmentation of infant brain images. *NeuroImage*, 108, 160-172.
6. Georgiadis, P., Cavouras, D., Kalatzis, I., Daskalakis, A., Kagadis, G. C., Sifaki, K., & Solomou, E. (2008). Improving brain tumor characterization on MRI by probabilistic neural networks and non-linear transformation of textural features. *Computer methods and programs in biomedicine*, 89(1), 24-32.
7. Papik, K., Molnar, B., Schaefer, R., Dombovari, Z., Tulassay, Z., & Feher, J. (1998). Application of neural networks in medicine-a review. *Medical Science Monitor*, 4(3), MT538-MT546.
8. Kwak, N., & Choi, C. H. (2002). Input feature selection for classification

- problems. IEEE transactions on neural networks, 13(1), 143-159.
9. Mammadov, M., & Tas, E. N. G. I. N. (2006). An improved version of back propagation algorithm with effective dynamic learning rate and momentum. WSEAS Transactions on Mathematics, 5(7), 872.
  10. Melssen, W., Wehrens, R., & Buydens, L. (2006). Supervised Kohonen networks for classification problems. Chemometrics and Intelligent Laboratory Systems, 83(2), 99-113.
  11. Specht, D. F. (1988). Probabilistic neural networks for classification, mapping, or associative memory. In IEEE international conference on neural networks, 1(2)4, 525-532.