# Spatial Domain Segmentation Algorithm for Tumour Detection and Wavelet Based Texture Analysis

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## Abstract

The most challenging and complex area of research in biomedical image processing is segmentation and analysis of brain tumour. It is proved by Statistics that amongst various brain ailments, brain tumour is may be fatal if it will be carcinogenic. The paper proposes a spatial domain segmentation algorithm for detection of brain tumour using multiple images of brain MR and k-means algorithm. Also a Brain Tumour Texture Analysis algorithm is proposed that uses fractal dimension, fractal area, and wavelet to classify type of texture present in brain tumour. The results obtained by those algorithms are found to be highly satisfactory and verified for ground truth by medical practitioners. The proposed algorithms were compared with other state-of-the-art algorithms and found to be better in terms of accuracy, precision and recall.

**Keywords:** MRI, Texture Analysis, Brain Tumour, Segmentation and Wavelet Transform

## Introduction

The information about tumor size, location and compression of adjacent brain structures can be obtained by Magnetic Resonance Imaging (MRI). Images can be analyzed using Computer aided tool for automatic segmentation and analysis of tumor due to high resolution. It is required efficient algorithms for segmentation and analysis of Brain MR Image.

The detection of brain tumor surface texture is challenging for researchers other than Brain tumor segmentation. In this paper image enhancement technique is utilized based on wavelet. It is used to scale the image resolution in a loss less manner. The implementation of a trained classifier using features such as fractal dimension, fractal area, and wavelet average is used to classify type of texture present in brain tumor.

Medical image analysis methodologies are required to computerize brain disorder diagnosis like brain tumour detection from MRI. The uncontrolled growth of the tissue cell in the brain causes brain tumour. The bio-medical imaging allows the doctor and researchers to analyze the brain anatomy by studying the brain without surgical invasion are computed tomography, Magnetic resonance imaging and Positron emission tomography.

The texture analysis or recognition has been an active research topic in the field of image processing and computer vision in almost three decades. In various areas like remote sensing, object recognition, mobile robot navigation, estimation of 3D surface area from 2D images, contour based image retrieval etc. the texture analysis is widely used. Different methods of texture analysis can be classified into three major categories: statistical methods, model based methods and structural methods. Each method has its own merits and demerits.

**Literatures Survey**

Bio-medical imaging is the domain of pathological investigation which combines different inter-disciplinary areas of technology like bio-medical engineering and physics and even medicine (in case of nuclear medicine imaging like PET-CT Scan), if required [1-2].

The segmentation is required for various clinical diagnosis like, detection, analysis and classifying various tumor categories, such as, edema, haemorage detection and necrotic tissues etc. For creating high contrast image having distinct gray levels for different cases of neuropathology MRI acquisition parameters are greatly adjustable [3]. The recent research focuses of segmenting MR images in biomedical image processing domain. In neuro-science segmenting of Magnetic Resonance image is required in diagnosis of neuro-degenerative and also various psychiatric disorders [20]. Computational cost, de-noising, quality of de-noising and boundary preserving capabilities in those methods are almost similar [4].

In frequency domain wavelet based methods is implemented for removing noise and preserving the signal. The use of wavelet on MR images biases the wavelet and scaling coefficient. The scaling coefficient become independent of the signal and is eliminated. Although in case having low Signal to Noise ratio images, liner details are not preserved.

A very accurate estimation of the probability density function (PDF) is necessary in probabilistic classification. Markov network or undirected graph model is a set of random variables that have Markov property that is defined by an undirected graph. Markov random field model is the statistical model that is implemented to model spatial relations which exist in the neighbor of pixels. [5-6] Image segmentation techniques use it to gain advantage of neighborhood information in the segmentation process, such as, in biomedical images most neighborhood pixels had the same class and effect of noise in segmentation is reduced.

There are many techniques for identifying textures in different contexts, like active con-tour model, shape distortion and normalization method, Fourier based shape descriptor method, and region based shape descriptor method [7-8].

A key role to identify the type of object present in the images is based on textural information. It captures the granularity and the repetitive pattern in the image. Fractals [9-10] are small pictorial patterns those tend to repeat in a textured surface.

The use of grayscale co-occurrence matrices (GLCM) by counting the number of occurrences of the gray levels at a given displacement and angle is another approach for texture analysis. Statistical quantities such as contrast, energy, entropy are computed from the GLCM to obtain the texture features [11-12].

**Proposed Methods**

To identify objects and their borders in the brain segmentation of image is made. It is the technique to segregate an image into different discrete segments i.e., sets of pixels, commonly known as super pixels. This process gives a label to every pixel of the image so that the pixels having same label share same visual characteristics. A three step refining segmentation algorithm is given here. The steps are as follows:

1. Initial segmentation using k-means algorithm.
2. Localization of segmented portion using local standard deviation.
3. Grid based fine grain localization using local standard deviation

It is then minimized the objective function using squared error function. The distance between a data point and cluster center are calculated.

The algorithm executes through the following steps:

1. The placing of K distinct points in original image are characterized by objects. These are getting clustered. Initial group centroids are signified by those points.
2. After the assignment of every object, recalculation of position of K centroids is executed.
3. Repeat Steps 2 and 3 until the centroids stop movement.

On successful execution of the above steps of image segmentation, histogram is generated of the segmented image. The generated histogram depicts distinct peaks in three different image gray levels, corresponding to gray matter, white matter and tumour. The subsequent segments of gray matter, white matter and tumor is extracted.

The outputs of the test case are shown in Figure 1 to Figure 6.

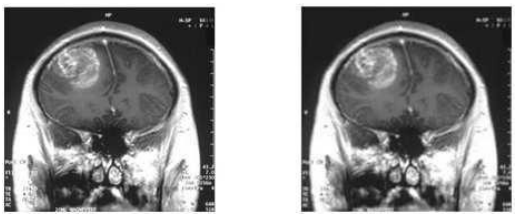


Figure 1: Input and Enhanced Image

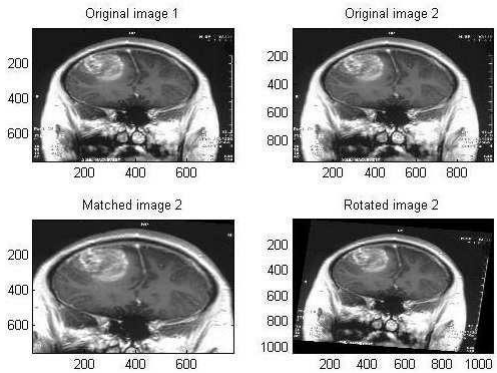



Figure 2: Registered Image

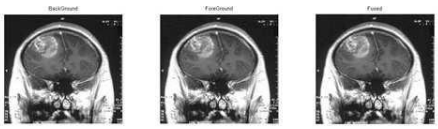


Figure 3: Fused Image

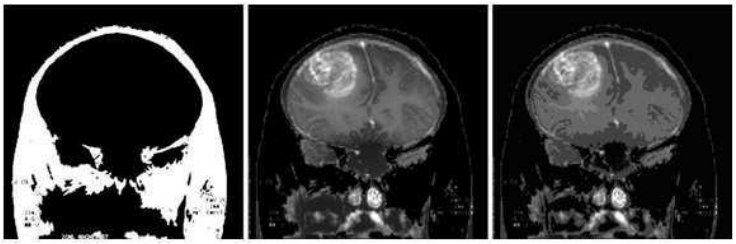


Figure 4 It shows Skull Mask, Skull Removed and K -Means Segmented Image

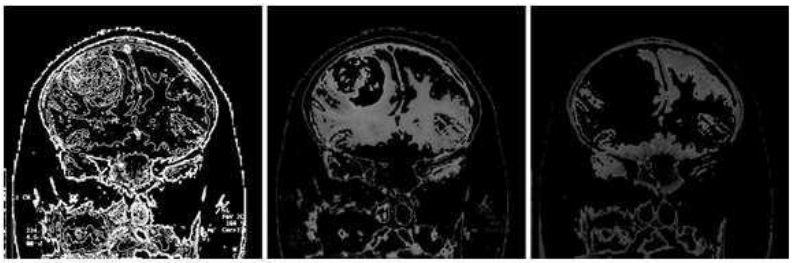


Figure 5: Local Standard Deviation, Gray Matter, White Matter

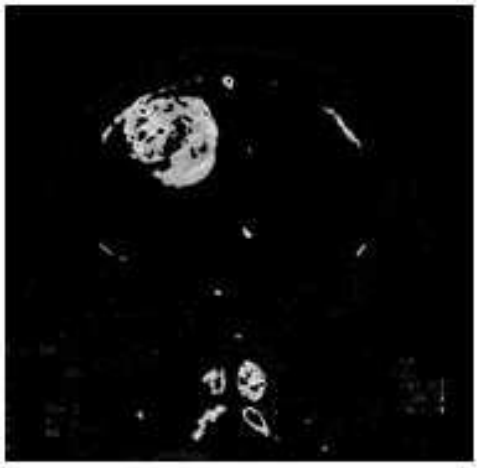


Figure 6: Identification of Tumour

The texture based algorithm for finding details of texture present in the brain is now described.

1. Input MR Image.
2. Equalize Histogram of the Image.
3. Separate out the Skull by Segmenting the Tumour from the brain.

a) The binary image has least intra class variance depending on thresholding.

b) The Skull less brain can be obtained by subtracting the threshold from image .

c) Divide the image in 64X 64 blocks

i. For each block among 4096 divided blocks, Daubechies wavelet transform is implemented to segment out the tumour.

ii. Tumour is segmented using thresholding based on the wavelet based features and the coordinates are stored for further processing.

iii. Morphological Operations are performed so as to display the actual positions of the tumor as an image.

d) It is required to find the texture information for the blocks which have a part of the tumor.

e) If there is a tumour in each block do the following:

i. Wavelet based resolution enhancement is implemented if the size of blocks are too small for finding tumor.

ii. The image so obtained from each block is decomposed using Haar wavelet transform to generate Average Image, Horizontal Detail Image, Vertical Detail Image, Diagonal Detail Image.

iii. Each Image is resized 10 folds.

iv. All the new images so obtained are fed to inverse Haar wavelet transform to get the new resolution enhanced image.

f) For each enhanced block

i. Find level 1 detail of the Haar, Daubechies, BiOrthogonal, Coiflet wavelet transform.

ii. Using Multilevel Otsu algorithm to find two level threshold values.

iii. Obtained Threshold values are used to generate two binary images.

iv. Fractal Dimensions are calculated using hausdorff method.

v. Using Fractal Dimension, Level 1 detail of the wavelets as features to identify the texture detail.

vi. Features are input to the earlier trained Discriminant classifier and the output class is registered for each block having the tumour part.

vii. With the knowledge of the registered class for each block, a grayscale image is generated showing the texture details with the different grayscale levels.

**Experimental Output**

The experimental analysis of textures values is shown in Figure 7. The comparison of existing methods with the proposed wavelet based algorithms are also presented from Table 1 and Table 2.

| Smooth Texture of Brain Tumor Surface with 100% Smoothness and 0% Roughness | | Rough Texture of Brain Tumor Edge with 60% Smoothness and 40% Roughness | |
|---|---|---|---|
| Feature values | Values | Feature values | Values |
| Mean Level 1 | 1.45772585 | Mean Level 1 | 1.34633022 |
| Area Level 1 | 239.1263369 | Area Level 1 | 235.9642857 |
| Dimension Level 1 | 1496 | Dimension Level 1 | 392 |
| Mean Level 2 | 1.498535377 | Mean Level 2 | 1.761117175 |
| Area Level 2 | 238.7133867 | Area Level 2 | 233.3372549 |
| Dimension Level 2 | 1748 | Dimension Level 2 | 25532 |
| Haar Average Level 1 | 99.99902423 | Haar Average Level 1 | 92.99393589 |
| Haar Detail Level 1 | 2.459757713 | Haar Detail Level 1 | 6.064112307 |
| Daubechies Average Level 1 | 98.74385556 | Daubechies Average Level 1 | 95.99413996 |
| Daubechies Detail Level 1 | 0.095614444 | Daubechies Detail Level 1 | 5.006003782 |
| Bi-Orthogonal Average Level 1 | 99.99901163 | Bi-Orthogonal Average Level 1 | 92.99392059 |
| Bi-Orthogonal Detail Level 1 | 2.698836768 | Bi-Orthogonal Detail Level 1 | 6.079409778 |
| Coiflet Average Level 1 | 98.45903827 | Coiflet Average Level 1 | 96.99443848 |

Figure 7: Obtained Texture Values for the Tumor

Gray Scale Values corresponding to different classes are shown in Figure 8.

| Class | Gray Scale Value (Black -> 0 & White->255) |
|---|---|
| Very Smooth (0% Rough 100% Smooth) | 42.5 |
| Moderately Smooth (20% Rough 80% Smooth) | 85 |
| Slight Smooth (40% Rough 60% Smooth) | 127.5 |
| Slight Rough (60% Rough 40% Smooth) | 170 |
| Moderately Rough (80% Rough 20% Smooth) | 212.5 |
| Very Rough (100% Rough 0% Smooth) | 255 |

Figure 8: Gray Level Indicating Different Classes

From the results as shown above it is observed that the texture of the tumor is given in comparison to daily used objects. This would help doctors to have an perception of the texture the tumor is having. It will help in diagnosis the type and state of the tumor by correlating to other clinical and pathological tests.

Table 1: Traditional segmentation algorithms with our wavelet based Algorithm are compared

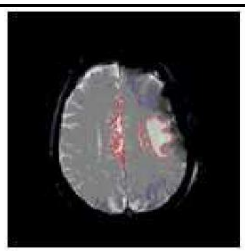
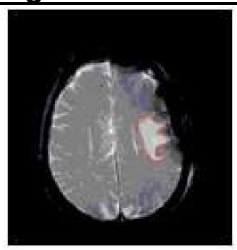
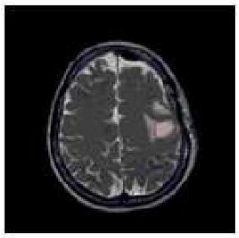
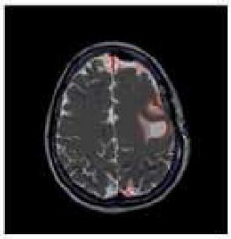
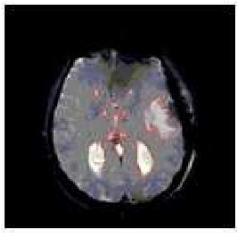
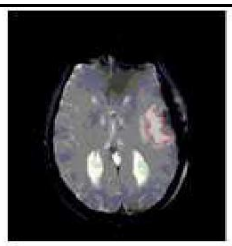
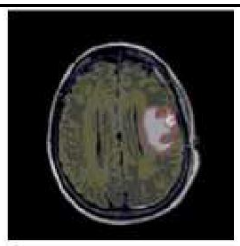
| **Outputs** | **Fuzzy C-means** | **K-means** | **Proposed Wavelet based Algorithm** |
|---|---|---|---|
| Output 1 |  |  |  |
| Time Taken | 4.891sec | 5.662sec | 6.823 sec |
| Output 2 |  |  |  |
| Time Taken | 5.141sec | 5.679sec | 6.596 sec |
| Output 3 |  |  |  |
| Time Taken | 4.797sec | 5.312sec | 6.231 sec |
| Output 4 |  |  |  |
| Time Taken | 4.912sec | 5.892sec | 6.927 sec |

Table 2: Comparison table of Five algorithms

| **Parameters** | **Fuzzy C-means** | **K-means** | **PZM + KSVM** | **WPTE + FNN +RCBBO** | **Proposed Wavelet Based Algorithm** |
|---|---|---|---|---|---|
| True positive (T P) | 0.91 | 0.91 | 0.95 | 0.96 | 0.99 |
| True negative (T N) | 0.93 | 0.93 | 0.91 | 0.89 | 0.98 |
| False positive (F P) | 0.07 | 0.07 | 0.12 | 0.12 | 0.02 |
| False negative (F N) | 0.09 | 0.09 | 0.11 | 0.1 | 0.03 |
| Precision | 0.93 | 0.93 | 0.88 | 0.88 | 0.98 |
| Recall | 0.92 | 0.91 | 0.89 | 0.90 | 0.97 |
| Accuracy | 0.94 | 0.92 | 0.88 | 0.89 | 0.97 |

The analysis of the comparison is also shown using bar graph comparing the five algorithms over seven parameters. The graph is generated based on the data given and is shown in Figure 9.

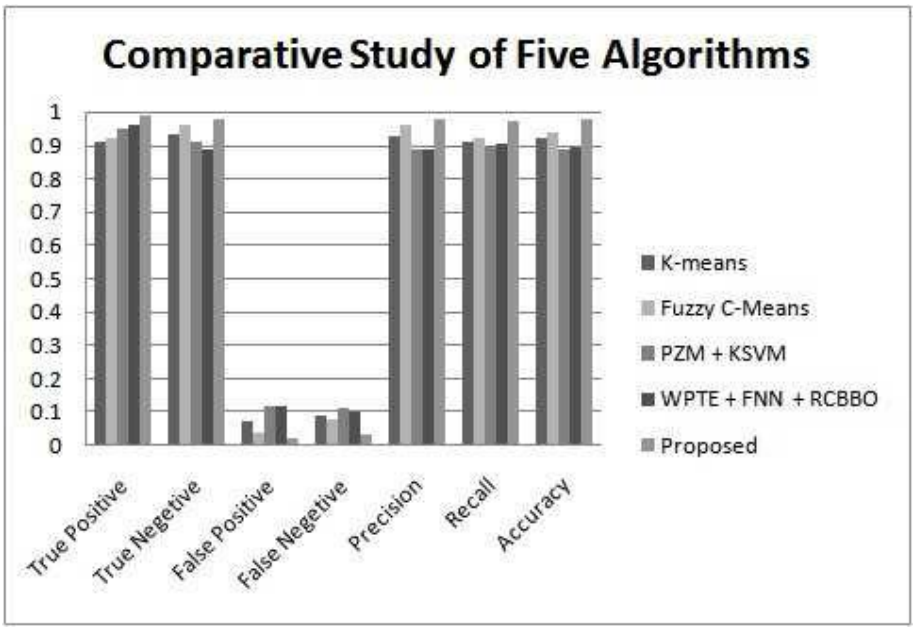



Figure 9: Graphical Comparison of Five algorithms with respect to seven parameters

## Conclusions

The proposed algorithms for Segmentation and brain tumour texture analysis is useful to doctors as well as to the diagnostic centre as it portrays the texture that tumour is having. Our algorithm defines the texture of tumour in reference to our daily known textures. The method utilizes both fractal analysis along with wavelet features to make the prediction much more firm in terms of accuracy. Generally, tumour appears as very smooth type and near the sides it becomes slight rough. The texture detail image will let medical practitioner know the type of texture of the tumour. This will help in diagnostics of the Brain tumour by correlating with other clinical tests and findings.

## References

1. K. Sinha and G. R. Sinha, "Efficient segmentation methods for tumor detection in MRI images," in Proceedings of the IEEE Students' Conference on Electrical, Electronics and Computer Science, pp. 1–6, IEEE, Piscataway, NJ, USA, 2014.

2. Y. Megersa and G. Alemu, "Brain tumor detection and segmentation using hybrid intelligent algorithms," in Proceedings of the AFRICON, pp. 1–8, IEEE, Piscataway, NJ, USA, 2015.

3. A. Hazra, A. Dey, S. K. Gupta, and M. A. Ansari, "Brain tumor detection based on segmentation using MATLAB," in Proceedings of the International Conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS), pp. 425–430, IEEE, Piscataway, NJ, USA, 2017.

4. A. Hanuman and K. Sooknanan, "Brain tumor segmentation and volume estimation from T1-contrasted and T2 MRIs," International Journal of Image Processing (IJIP), vol. 12, no. 2, pp. 48–62, 2018.

5. C. Zhang, X. Shen, H. Cheng, and Q. Qian, "Brain tumor segmentation based on hybrid clustering and morphological operations," International Journal of Biomedical Imaging, vol. 2019, Article ID 7305832, 11 pages, 2019.

6. P. Qian, H. Friel, M. S. Traughber et al., "Transforming UTE-mDixon MR abdomen-pelvis images into CT by jointly leveraging prior knowledge and partial supervision," IEEE/ACM Transactions on Computational Biology and Bioinformatics, 2020.

7. P. Qian, Y. Chen, J.-W. Kuo et al., "mDixon-Based Synthetic CT Generation for PET Attenuation Correction on Abdomen and Pelvis Jointly Using Transfer Fuzzy Clustering and Active Learning-Based Classification," IEEE Transactions on Medical Imaging, vol. 39, no. 4, pp. 819–832, 2020.

8. Y. Jiang, K. Zhao, K. Xia et al., "A novel distributed multitask fuzzy clustering algorithm for automatic MR brain image segmentation," Journal of Medical Systems, vol. 43, no. 5, pp. 118:1–118:9, 2019.

9. Z. Zhang and E. Sejdić, "Radiological images and machine learning: trends, perspectives, and prospects," Computers in Biology and Medicine, vol. 108, no. 6, pp. 354–370, 2019.

10. Wang S, Meng M, Zhang X, Wu C, Wang R, Wu J, et al. Texture analysis of diffusion weighted imaging for the evaluation of glioma heterogeneity based on different regions of interest. Oncol Lett. 2018;15(5):7297–7304. pmid:29731887.

11. Mohan G, Subashini MM. MRI based medical image analysis: Survey on brain tumor grade classification. Biomed Signal Process Control. 2018;39: 139–161.

12. Vallières M, Freeman CR, Skamene SR, El Naqa I. A radiomics model from joint FDG-PET and MRI texture features for the prediction of lung metastases in soft-tissue sarcomas of the extremities. Phys Med Biol. 2015;60(14):5471.