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# A Study on Various Segmentation Techniques for Analysing Brain Mr Images

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**ABSTRACT**

Image segmentation is an imperative handing out step in many images, video and visual computer applications. Image segmentation enhances the problem-solving capabilities of physicians and reduces the time required for precise diagnosis. The intention of this paper is to go over the current published segmentation and classiûcation techniques and their state-of-the-art for analysing the human brain magnetic resonance images (MRI). The review reveals that analysis of human brain MRI images is still an open problem. Widespread research has been done in generating many approaches and algorithms for brain image segmentation, but it is still complicated to assess whether one algorithm provides more precise segmentations than another, for a particular image or set of images or for a whole class of images. In this paper various segmentation techniques and their limitations are discussed.

***Keywords:*** Support Vector Machine (SVM), Region of Interest (ROI), Ant Colony Optimization (ACO), Live Wire Algorithm, Gossiping Algorithm.

## 1. INTRODUCTION

Image segmentation techniques are broadly classified into manual, semi-automatic, and fully automatic ones. Manual segmentation, is good at object recognition, but uses more time in execution and identifying precise boundary requires more effort. Fully automated methods, are effective but suffers from failure related to identifying ROI, resulting in imprecise segmentation. While semi-automatic techniques on the other hand provide both good organization and exactness by allowing users to do the object acknowledgment and allows computers to capture the required details. Thus, semiautomatic image segmentation techniques are of sensible use for a range of applications including medical image analysis, digital image composition, key extraction, etc [1]. Brain tumor is one of the most important causes for the amplified escalation in death among children and adults. Brain tumor is a cluster of anomalous cells that grows within brain or roughly around the brain [2], [3]. Many varieties of brain tumors exist. Some brain tumors are benign, and some malignant. Brain image segmentation is a valuable progression in brain volumetry, in this process the three foremost brain tissues, white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF) are identiûed. The labour-intensive slice by slice segmentation is a relatively tricky and lengthy task, because of the geometric complexity of the human brain cortex [2].

Brain imaging techniques permits doctors and researchers to inspect functionality or problems within brain, devoid of invasive neurosurgery. There are a numerous techniques that are acknowledged and safe to be used in research conveniences and hospitals all over world. The modalities available allow doctors and researchers to learn about brain by analysing it non-invasively. Computed tomography (CT), positron emission tomography (PET) and MRI provides quality knowledge about brain tissues, from a range of excitation sequences. In comparison with many other imaging techniques, MRI shows higher dissimilarity for various brain tissues. MRI is resourceful in the application of brain tumor uncovering and findings, due to the elevated gap between soft tissues, high spatial resolution and has advantages like no–radiation and non-invasive technique.

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MRI is considered the medical imaging process of preference when soft tissue demarcation is necessary. This is particularly factual for any effort to pigeonhole brain tissues. Radiologist second-hand this method for getting a mental picture of internal structure of brain. MRI provides rich information about human soft tissues anatomy. MRI helps for getting opinion of the brain tumor. Images obtained by the MRI are used for analyzing and studying the behavior of the brain. The strength of the MRI signal depends primarily on three molecules. Other two parameters are T1 and T2 relaxation, which reûect different features of the local environment of individual protons. The 'pathological' T2 scan is useful for locating the lesioned region in the brain. The 'anatomical' T1 scans usually have the best scan resolution, and are useful for localizing anatomical structures. Brain tumors vary depending upon its distinct components like location, shape, size and image intensities.

The most important input of this paper is to go over the most recent segmentation mechanisms and their state-of-the-art. Segmentation depends on color, shape, region of interest, by combining various factors to get multimodal effect and also based on trained or untrained methodologies as shown in Figure 1.

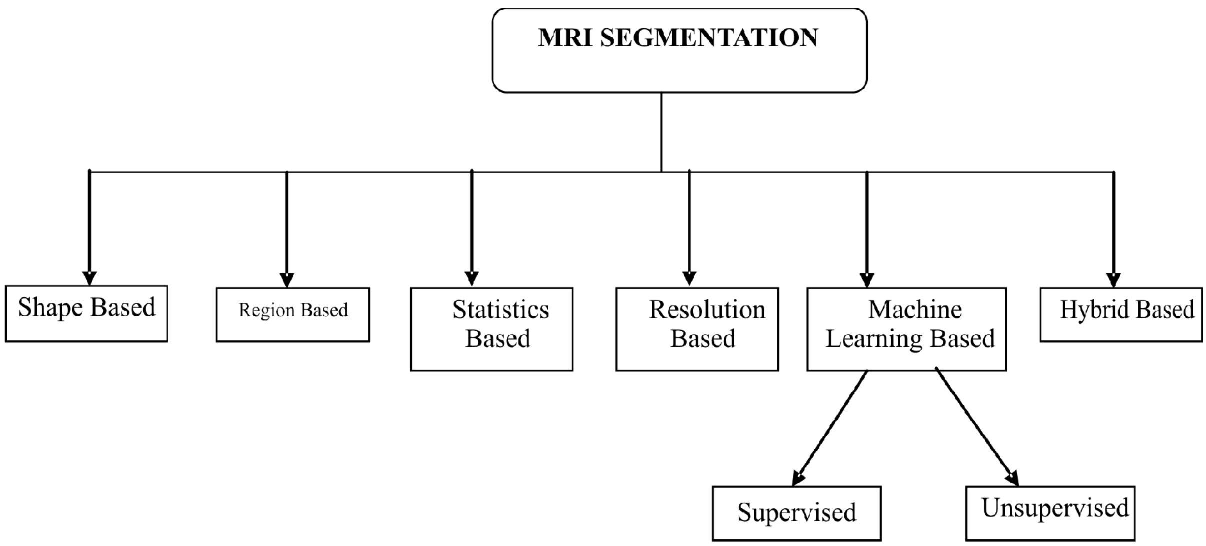


**Figure 1: Various Segmentation Approaches**

## 2. SEGMENTATION CLASSIFICATION

### 2.1. Based on color

In [3], the author proposed a brain volumetry technique which emphasised on the usage of segmentation based on VFC (Vector Field Convolution) mechanism and SVM (support vector machine) approach as classifier of MRI images. This approach showed advantage over other methods because of its simplicity, no user interaction and ability to handle first and last slice of the MRI images. Drawback of this approach is its inability to handle non uniform MRI images, complexity in training SVM classifiers and the evaluation is based on a data set of 10 noisy images.

Marx & Brown (2000) suggested a progressive livewire approach to segment consecutive images by combining Snake and Livewire algorithms. Finding minimal cost paths is the advantage but is also the reason for drawback since finding a better cost function is a central issue. Local superiority is a major challenge of this approach [4].

G-wire semi automatic segmentation method proposed by Kang (2005) for segmenting 3D images which uses multidimensional graph that allows internal and external feature incorporation into cost function to make it liable to handle images in an unified manner. The advantage of G-wire approach is fast smooth and precise segmentation results over noisy images of different sizes and complexities [1].

Yousefi et al (2012) combined Ant colony optimization technique and gossiping algorithm to find the best shortest path among neighbouring region to automatically segment single and multispectral MRI images. The hybrid approach improves the speed and accuracy of the result but with overhead of complexity [5].

Dubey & madasu (2009) proposed a semi-automatic segmentation to effectively identify tumor size as it is consider as an important diagnostic parameter for treatment of brain tumor. This approach overcomes the drawback of automatic method that has a lower level of agreement with the human experts compared to the semi-automatic method. The semi automated method generates results that have higher level of agreement with the manual raters. Better performance is achieved with small dataset, is the drawback that need to be improved in this approach [6].

### 2.2. Based on Region

Tang et al (2000) the proposed multi-resolution edge detection and region selection segmentation method reduces noise in homogeneous region (White matter). If combined with proper method to identify edginess accurately this approach may provide accurate results in identifying potential areas of infection [7].

Fully automated brain extraction approach based on T2 MRI proposed by Somasundaram & Kalaiselvi (2010) reduces the size of MRI which reduces the transmission time of the image as well strips the skull much faster than many other approaches, thus finding a place for this approach in telemedicine technologies[8].

Slantlet transform based approach suggested by Mitra & Amitava(2006) emphasis on classifying MRIs as normal or abnormal by computing intensity histogram and process them by applying slantlet transform to perform brain classification. This works well with gray images but complexity might increase with RGB images is identified as the drawback of this approach [9].

Jafari (2011) proposed an approach that uses seeded region growing segmentation and neural network classification and obtained best identification when applied on 2D axial slices of 10 dissimilar patient data sets[10].

### 2.3. Based on Statistical

Donoso et al (2010) approach of modifying Expectation algorithm produces more accurate segmentation results when applied to over 32 real MRIs. It shows 95% accuracy with respect to false negative identification and elimination but suffers a lot with respect to false positives [11].

### 2.4. Based on Multi resolution

Fuzzy curvelet approach of Jaffar et al (2011) expects no prior knowledge about the input and performs well without human interference. So far it is applied for segmenting MR images and need to be expanded to detect brain tumors cells [12].

### 2.5. Based on Machine Learning – Supervised & Unsupervised

Ortiz et al (2013) presented a segmentation method that uses hybrid artificial intelligence technique, which effectively extracted features from given image that is used by effective classifier to classify the extracted features. The segmentation process efficiency is improved by replacing SOM by GHSOM methodology [13].

Neural network based approach by Zhang et al (2011) showed accuracy in terms of classifying MRI images as normal or abnormal. This approach shows promising computation time, it still needs improvement to handle other varieties of image; multiple classifications have to be applied on given set of input image [14].

Weili et al (2009) approach to segment medical images based on a technique devised through the combination of improved threshold function of PCNN and 2D Tsallis entropy. It shows a better precision in image segmentation and has stronger adaptability, has to be improved in such a manner to effectively segment complicated medical image [15].

The false positive detection approach of yamamoto et al (2010) proves effective in diagnosing MS lesions in 2D MR images by taking advantage of three methods, such as rule-based, a level set method and support vector machine. Improvements have to be made to the above mentioned methodology to effectively segment 3D images of various image quality with various variety of MS lesion [16].

## 3. INFERENCE FROM THE SURVEY

The constraints identified from the analysis of the above mentioned papers and the fact that segmenting the MRI images to identify the target region proves to be a complex task. Therefore, the problem of segmenting MRI images for inferring knowledge from them has been a subject of intensive research. However, there are still many open research issues, outlined below:

1. Classifying large datasets from collected from different sources and with different image quality.
2. One generalized solution for various MRI images with difference in image thickness, color contrast, intensity variations, noise accumulation etc.
3. Selection of more efficient feature for better classification.
4. Use of trained data set or training the data set efficiently to get better performance.
5. Combining more than one machine learning technique to device a hybrid approach.

## 4. CONCLUSION

Enormous growth in the field of machine learning and computational intelligence has paved way to attraction of using segmentation techniques for studying and classifying brain tumors. Analysis and classification of brain tumor is a major area of research in medical image mining. Review of current trends in the field of segmentation, extraction of features, classifying the images based on the algorithms is discussed. The review depth has its footing set from 2000 to 2014.

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