

SELF - ACTIVATED SEGMENTATION PRACTICES OF BRAIN TUMEFACATION IN MR SCAN IMAGES: A STUDY

B. Perumal

Department of Electronics and Communication Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Virudhunagar (Dt), (India).

E-mail: palanimet@gmail.com

ORCID: <https://orcid.org/0000-0003-4408-9396>

R. Sindhiya Devi

Department of Electronics and Communication Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Virudhunagar (Dt), (India).

E-mail: sindhiyadevi14@gmail.com

ORCID: <https://orcid.org/0000-0002-7529-6438>

M. Pallikonda Rajasekaran

Department of Electronics and Communication Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Virudhunagar (Dt), (India).

E-mail: mpraja80@gmail.com

ORCID: <https://orcid.org/0000-0001-6942-4512>

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ABSTRACT

To segment a tumefaction of brain images obtained from any of the imaging modalities is a lofty goal owing to the varied shape, locality and measure of tumor. This segmentation process can be done manually by a Doctor or otherwise can be done automatically using computer aided diagnosis. Self – Activated segmentation of brain tumor is nothing but the separation of the tissues that are not related with the tissues within the brain case akin to the regions with myelinated nerve fibers without dendrites, portions of nerve fibers with dendrites and the cerebrum area along with the cerebrospinal fluid (CSF). The various imaging modalities are the scans from the radiology with emitting positrons (PET), multiple X – rays (CT) and through Magnetic Resonance (MRI). In this paper, an overview of recent automatic brain tumor segmentation techniques of MRI and the advantages of multimodal imaging techniques has been explained. The segmentation techniques such as thresholding, edge based, morphology based, watershed, k means and markov random method are the conventional tactics of segmentation that are addressed. Also, the advanced segmentation methods such as region growing, genetic method, fuzzy clustering, deformation, atlas method and artificial neural network are also discussed. Moreover, the hybrid methods that have different combination of genetic algorithm, artificial neural networks and SVM are also considered. Among all the methods, the hybrid methods are found to be better as they provide the beneficiary factors of every method involved. But one should be aware about the algorithm's robustness and accuracy.

KEYWORDS

Tumor, Segmentation, Automatic, Multimodal Imaging, MRI Images.

1. INTRODUCTION

Tumor arises when the cells of certain portions of our body starts growing abnormally. Detecting tumor in the early stage is of the greatest significance for the survival of life. Also, the size and shape of the brain tumor decides the treatment modality. Over 120 different types of brain tumor are in existence and are possibly graded as primordial and metastatic brain tumor. The primary tumors do not spread to another part of the body and stay within the brain. Statistically, it is found that primary tumor is found to be developed more in older adults and children. The meta-static tumor taints the extant organs of the body from the region of its origination. It is more prevalent in fully – grown people in comparison with offspring.

Based on the characteristics, tumors can be categorized as benignant and virulent. The benignant tumors are leisurely developing and are destructive to a lesser extent. The malignant tumor is rapid growing and life threatening.

The ways and means of dissociating an image into multitudinal portions are said to be segmentation. And it is seen that the pixels within the region have same characteristics. During the preprocessing stage like segmentation separation of different tumor tissues from normal tissues is done. In practical life, segmentation of brain tumor is performed laboriously. But this laborious technique of splitting the tumor yields extended time span and may sometimes create impreciseness in its results. With the intension of doing a favor for medicos in the diagnosis and treatment of tumor the research in automatic segmentation techniques of brain tumor is getting more important.

2. MATERIALS AND METHODS

2.1. COVENTIONAL SEGMENTATION TECHNIQUES

MRI is a noninvasive diagnosing imaging modality. It affords certain benevolent lineaments like multi – planar capabilities. Separation methodologies are abundant in the assessment surveys. A few among the prevailing conventional tactics for segmenting brain tumor are addressed henceforth.

2.1.1. THRESHOLDING METHOD

Thresholding is one of the segmentation techniques which correlate the brightness of the pixels with the thresholds which may be one or many. The local and global thresholding (Lin *et al.*, 2012) are their prominent categories.

We can distinguish the tumor region from its backdrop by considering the selected threshold and we can utilize this bifurcation for segmentation. The object portion with tumor is allocated the binary value 1 so that those picture elements satisfy the selected threshold value. Others that are insufficient when compared with the threshold value are allocated with the binary value 0 and they are the background pixels (Khan & Ravi, 2013).

If an image possesses homogeneity in its intensity levels, then splitting up with the global thresholding paves a better way. Over segmentation and under segmentation are possible with thresholding means of separation, which may be a major drawback. The global thresholding may cause brighter and darker patches on the grounds of inhomogeneous intensity levels.

2.1.2. EDGE – BASED METHOD

Edge based approaches are many in number that includes Canny, Sobel and Prewit. Canny method (1987) is obtained by simply adding up some alteration in the Sobel method. Canny edge detector implements Gaussian in its criteria so that the consequence of noise could be reduced. It indulges enhanced sharp edges in comparison with other methodologies.

In the segmentation of medicating imagery, we have an alternative which is the Chan and Vese Active contour model (2001). We can call it in other words as Active contour model. The interior contours and the undefined boundary objects are competently recognized by this methodology.

The steepness of edge of the image is detected by the snake model, which is a customary edge indicator. The images with inhomogeneous intensity that need the betterment results use this model. Generally, the edge – based segmentation approach is uncomplicated. The edge-based segmentation produces open contour and also the edges are sensitive to the threshold values.

2.1.3. MORPHOLOGICAL BASED METHOD

The process in which the anatomical features of the image are employed is the morphology-based methodology. The utilization of this method is to extract the data from the image centered on their shape presentation. The most basic morphological operations used are erosion and dilatation. They are contrast to each other. It means that the resultant pixels of these processes are least possible and the uttermost values of the total pixels that appears nearby the input picture element. In other words, we can say that, in a binary image, if any pixel is allotted the value 1, then the dilation makes the resultant to be '1' and it is '0' in case of erosion.

The manipulation of the erosion algorithm is for shrinking while dilation is for developing the image size. The morphological based technique has the tendency to segment tumor even in images with lesser intensity. This process incorporates some steps that include image enrichment, generating new samples, extrication of color plane and morphological methodology to get the Region of Interest (RoI) from the image (Sudharania, Sarma, & Prasad, 2016). These are employed in order to eliminate picture elements of reduced frequency and border portions.

2.1.4. WATERSHED METHOD

The working of the watershed algorithm is similar to the action of water on the landscape. We know that the partitioned landscape is of separated portions by dams and reservoirs. The water flows from various troughs at a centered region where the dam is present. The flow of water stops at once when the water touches the tip of the landscape. Therefore, every portion of landscape has a dam and resembles the watershed technique. So, an exhaustive silhouette is formed which needs no jointure.

Over – segmentation is the principal drawback of this method. In order to subjugate this confinement, images should be processed both at the pre – stage and the post – stage of segmentation to get satisfactory results. Pandav (2014), in her paper, propose Marker – Controlled Watershed Segmentation which utilize floods and image gradient initiated from the notches instead of localized least for its dissection which brings about superior outcome

from heterogeneous zones simultaneously. It generates the entire lineament of the segments and hence it needs no jointure which is an added advantage.

2.1.5. K – MEANS CLUSTERING

The clustering technique which is the simplest and the merest mean of segmenting image is the K-means clustering algorithm (Kamble & Rathod, 2015). In this process of clustering, k bands are initialized first and then for each band, we develop a barycenter or centroid in a random manner. The centroid values are changed depending on the values of the neighborhood bands until the stability is reached. The new centroid is assigned in such a way that it is taken from the mean of every object in every barycenter.

2.1.6. MARKOV RANDOM FIELD METHOD

The model which converts the structural data into the procedure of crowding is the Markov random field (MRF) model. In this model, the overhanging of split – up and the impact of noise are diminished. Hence, it is a user – friendly technique in segmenting medical images.

A novel method that utilizes the conjoint spatial features to extricate the configuration with Gabor decomposition, for the fragmentation of tumor from the backdrop is explored in Zhang, Brady, and Smith (2001). After this, the outcomes were additionally purified with this methodology as it categorizes every sub – class of the image. But it is a perplexing procedure. Despite that, it is an effectual method to work with images having inhomogeneous intensity.

2.2. ADVANCED SEGMENTATION APPROACHES

There are some advanced methods of segmentation. Some of those advanced techniques are discussed in the following section.

2.2.1. REGION GROWING METHOD

The process which involves the grouping of regions according to the similarity of the pixels until each pixel is allocated to a group is called the Region growing method. We start this operation by electing a seed point. The seed selection is done either automatic or manual. Similar neighbors of the chosen seed are added to the region. We repeat this growing of regions each seed is allocated to a region. The region growing when used along with

fuzzy logic to get a knowledge – based region growing is always profitable (Lin *et al.*, 2012). Here, different objects are grouped with the geographical data and equivalence from the multimodal images, fuzzy logic and homogeneity of the images are employed in finding out the initial seed.

The region growing methodology on the basis of its image texture is explained in Charutha and Jayashree (2014). We can consider the threshold value of both the intensity and texture for the extraction of brain tumor in medical images. As in every method, it also has its own merits and drawbacks. Its merit is that the similarity of pixels could be easily measured and tracked, while it has a demerit that it is more complex in selecting initial seed point and is susceptible to noise.

2.2.2. GENETIC METHOD

The method used for solving both the guarded and unguarded problems for finding optimization and it is a selection process gleaned from the natural transformation (Fan, Jiang, & Evans, 2002). We use chromatins in the genetic algorithm with the purpose of expressing the population. We can rejuvenate the population of individuals repetitiously by the usage of terms like alteration and crossover with a selection operator. The function that is meant for assessing population in the genetic method for the optimization is called fitness function. We use this genetically dependable algorithm for effective optimization of the segmenting portions of MRI images (Chandra & Rao, 2016).

In the methodology described in Chandra and Rao (2016), they used K – means to get the bands for the population at the initial stage. The barycenter or the centroid is estimated by a specific fitness function. The exchange of healthy chromosomes with the weaker ones is done by using crossover and mutation. If the problem is of more difficulty, then the genetic algorithm provides a better solution.

2.2.3. FUZZY CLUSTERING

Fuzzy clustering is one of the advanced clustering techniques in which the grouping is mainly based on the membership function (Oliveira & Pedrycz, 2007). The membership function in the fuzzy logic owns a value within the bounds of 0 to 1. This value of the factor shows the homogeneity amongst the picture element and its barycenter. The process of fuzzy

clustering allots a membership function for each and every picture element determined by its characteristics. The pixel is said to be located near the barycenter if it possesses the value 1. The vicinage fascination with reference to the locale and the pixel's connection to adjacency pixels surge the potential of Fuzzy C Means (Selvakumar, Lakshmi, & Arivoli, 2012).

The extent of the most appropriate value along with the scope of connection between the pixels are established by making use of the combined Genetic algorithm ad Particle Swarm algorithm. Normally, there are two main stages in the system that includes the analysis and evocation. The main disadvantage of the fuzzy based clustering is that the non – usage of geometrical data for segmenting tumors (Ain, Jaffar, & SunChoi, 2014).

2.2.4. DEFORMATION MODEL

The deformation model better suits for locally changing environment since it befalls in the variable image object. This model resembles a closed curve in 2D while a closed surface in 3D images. This model is of two major types. They are the parametric deformation where the model is snakes which are the active outliers and the geometric deformation.

A method that uses Chan Vese Active contour model also called as Active contour model is specified in Chan and Vese (2001). It recognizes the innards and the other objects without gradient undefined boundaries. A traditional snake model edge which depends on the gradient value of the image is further improved by Chan Vese model. This model gives better yield for images with similar inhomogeneity.

2.2.5. ATLAS METHOD

An atlas is nothing but a reference image that is previously segmented by an expert for the tumor extraction in unobserved images. In the atlas dependable method, we first register both the atlas model and the goal image to be segmented. Then we have to map the model with the target image for effective segmentation. A novel technique without any mesh to design the atlas for well – conditioned brain imagery along with a reformed atlas for a diseased or morbid brain image has been projected in Bauer *et al.* (2010).

In order to embellish its accuracy, the tumor's locale along with the reason that provokes the tumor growth should be equipped with the atlas. In case of segmentation in multiple regions, (Al-Shaikhli, Yang, & Rosenhahn, 2014) used an adapted multileveled set of articulation with the atlas data of the statistical provost graph. Diaz and Boulanger (2015) used Total Lagrangian Explicit Dynamic (TLED) method to tackle a massive disfiguration devoid of giving up. The atlases for the deformed brain image employ the genuine pattern of the tumor rather than employing erratic pattern (Dia & Boulanger, 2015). The initial seed point need not be initialized in this technique which in turn multiplies the vibrancy. Also, the processing time is diminished because of the parallel processing system. Its performance shows the merit while its demerit is that more time span will be taken for the construction of atlas models.

2.2.6. ARTIFICIAL NEURAL NETWORK

The main idea of the artificial neural network (ANN) classifier is machine learning. They are the brain – stimulated systems in such a way that it resembles the same way by which the human beings learn. It comprises various nodes including the insertion node, transitional nodes and the unexposed nodes.

We need to train the machine to determine the worth of the parameter factors. The region of interest (RoI) is systematized by employing the modified probabilistic neural network (PNN) with linear vector quantization (LVQ) modeling process as shown in Song *et al.* (2007). Every RoI is designated with a combo of countenance and a counterweight which are meant for deriving an interconnected structure with reference to LVQ. It also has its own restriction that the size of the network holds the difficulty criteria. It means that the complexity increases with the loftiness in its size, since it requires surplus tutoring.

2.2.7. HYBRID METHOD

The best characteristics of different methodologies are combined together to get the hybridized method. Those hybrid methods are faster with greater accuracy. The pulse-coded neural network (PCNN) if enhances, it will improve its reality feature of simulation. The primary firing involves the selection of neurons as its seed points for region growing and the secondary firing grows the region by summing up the seeds with feed forward back

neural network (FFBNN). The feed forward process is done to reach the uniformity in its input. Stationary wavelet transform (SWT) is exercised for getting the sub images with the data of multiple resolutions (Ortiz *et al.*, 2013).

Spatial filtering along with LVQ is done with the purpose of extracting numerical features and regulating of the resultant image. Here, the segmentation is performed with Content – Based active contour model (Sachdeva *et al.*, 2012). Genetic Algorithm helps in reducing parameters with higher dimensions. While comparing the hybrid process of GA and SVM with GA and ANN, the prior is good in speed while the latter is better in its accuracy. The hybrid method slips in the step that it possesses higher computative expenses.

3. DISCUSSION

Segmentation methods are becoming more growing day by day and gaining importance in clinical research. In spite of the numerous contradictions in the process of segmentation over MRI imagery, they are blooming nowadays. One such contradiction is the need of transpicuousness. Another question is about its accountability to understand the need. Some other conflicts include laboring antiquity and movement antiquity. The impact of sectional measure and the inhomogeneous intensity are also the pervasive problems in the splitting up of the brain tumor. The deviation in its structure such as shape, size and the locale of tumor also affects segmentation results. The value of Signal to Noise Ratio should be low so that the resolution will be elevated. So, the relics must be eliminated by using the appliances with higher resolution and worthier filtrating which causes no loss in its anatomy. The tumor has its impact not only in the affected area but also the surrounding portions. This shows the fact that the segmentation of every affected region is necessary. Hence, further awareness should be paid on the robustness and accurateness of the algorithm. The algorithm's effectiveness can be validated by utilizing ground truth images.

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