

Brain Tumor Detection, Demarcation and Quantification Via MRI

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Abstract:

The paper presented explains how the gradient differential plays an inseparable part in demarking the tumor in brain. Areas that do not match with the benchmark set are skipped by the algorithm i.e. eminent entropy and intensity which are considered as major feature of tumor identification. The picture is finally rebuilt by evaluating regional maxima and extended maxima transformation which at the end gives us the most impressionable part of tumor. To generate final output the algorithm takes just 3.218 seconds (as an average statistics). At the end the proposed algorithm detects the tumor with high accuracy.

INTRODUCTION:

A lump of body tissues which took birth by continuous expansion of peculiar cells is termed as tumor. Normally, in human bodies everyday thousands of cells are born then they get oldie, then die and finally are being replaced by the cells which are freshly born. Due to the disturbance of the cells which occurs in situation of diseases like tumor and cancer these cells starts' growing up even after the body does not need them. They does not get expire as in the case of normal cells. As more and more cells joined up the effected parts converts into a cyst.

In broad classification there are basically two types of tumor i.e. primary and secondary tumor. Cell tissues who are generated from the brain parts are which later on converted into tumor are classify a primary tumor and tissues which are formed from the different parts of the body causes cancer are secondary tumors. Not all tumor are dangerous, harmless tumors are called benign primary tumor and on the other side cancer causing brain tumors are called malignant. Benign brain tumors can easily detected as they have clear outlines around them and are not strongly immense into the brain cells. The growth of malignant tumor is faster than benign tumor. A malignant brain tumor ordinarily grows faster than benign tumors.

This paper focused on the brain tumor detection in brain and also calculates the effective area. Brain tumor detection is a irksome task as it requires the skillful techniques to exactly identifying the affected area. This method has to detect, locate and evaluate the tumor effected portion. The location of benign brain tumor is an easy task as it has a natural outlining around it and does not have deep marks as in case of malignant tumor. The brain image is classify into number of parts when MRI is done and through analysis are performed on the image to find the tumor part. The type of tumor is discriminated by analyzing the parts if there is benign tumor it is seen in some parts of image only but if tumor is malignant in nature it goes into deeper parts of tissue. This property helps us to identify the type of tumor and also we have to study some other prominent features to generate the exactly tumor portion which cause abnormality in the brain functions.

II. RELATED WORK:

Tumor segmentation from magnetic resonance (MR) images by hybrid approach helps to detect tumor and tumor treatment by tracking the tumor growth. Nobuyuki Otsua [1] has given a technique of automatic threshold the picture segmentation. Michael R. Kaus et.al [2] had made an automatic brain tumor analysis method which was gives precise results as compare to manual segmentation with 3-D magnetic resonance images. Lynn M. Fletcher-Heath et.al [3] in their research stated that the automatic analysis method which separate brain tumors which are non-enhancing from cells in MR images which helps in calculating tumor size over time. Alain Pitiot et.al [4] presented a fully automated technique for medical figures. Djamel Boukerroui et.al [5] proposed strong method to specially analyse noisy images, within a Bayesian framework. Kristin R. Swanson et.al [6] Inspects the aspects of advancements in mathematical modeling of gliomas in the study. Yuri Boykov et.al [7] gives low/high flow graphs to determine energy in low level vision. Stuart S. C. Burnett et.al [8] developed a deformable-template

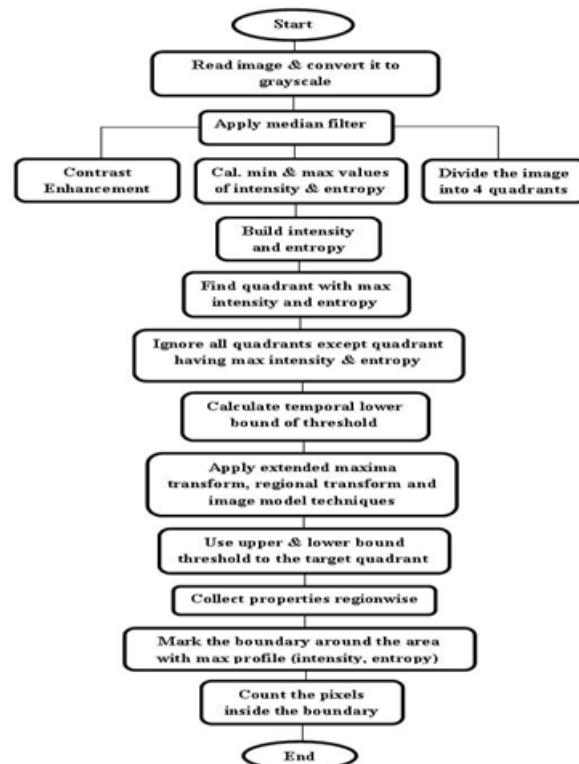
algorithm for the semiautomatic delineation of normal tissue structures on computed tomography images. Weibei Dou et.al [9] proposed a framework of fuzzy information fusion in this paper to automatically segment tumor areas of human brain from multispectral magnetic resonance imaging (MRI) such as T1-weighted, T2-weighted and proton density (PD) images. Kyungsuk (Peter) Pyun et.al [10] has developed a multiclass image segmentation method using hidden Markov Gauss mixture models (HMGMs) and provide examples of segmentation of aerial images and textures.

Hassan Khotanlou et.al [11] has presented a new general method for segmenting brain tumors in 3D magnetic resonance images. Under the scope of this paper the basic features of tumors demarcation such as texture information have not been taken into consideration while designing the algorithm. Jason J. Corso et.al [12] presented a new method for automatic segmentation of heterogeneous image data that takes a step toward bridging the gap between bottom-up affinity-based segmentation methods and top-down generative model based approaches. T.

Logeswari et.al [13] in their paper had described a segmentation method consisting of two phases. Sufyan Y. Ababneh et.al [14] has proposed a new, fully automated, content-based system is proposed for knee bone segmentation from magnetic resonance images (MRI). P. Narendran et.al [15] tried to segment brain tumors, their components (edema and necrosis) and internal structures of the brain in 3D MR images.

Sudipta Roy et.al [16] in their work introduced a fully automatic algorithm to detect brain tumors by using symmetry analysis. Mukesh Kumar et. Al [17] used the texture analysis and seeded region growing method which is based on texture of the MRI. Although the author tried to minimize the total execution time of this method but still it takes minimum more than 8seconds to provide its results.

PROPOSED WORK:



Step 1: Read and convert the input image from RGB to greyscale image: An image or digital image is just a data arranged in a form of matrix. It has numbers as data which demonstrates red, green, and blue and their modifications at a peculiar location. An image is read by using imreadcommand is used and through this command the image from graphics file is being read. Next task is the conversion of colored image into grayscaleimage and for that matter there are 2 key mechanisms: first one is the average mechanism and the second mechanism is weighted or luminosity mechanism. The very first method i.e. average method is very uncomplicated one as it evaluates the grayscale image by calculating the mean (average) of red, green and blue.

$$\text{Grayscale image} = (R + G + B / 3) \dots\dots\dots (1)$$

But the above mentioned conversion has a major drawback that it turns the image black because of determining the average of the three colors red, green and blue. Moreover these 3 colors have 3 various wavelengths that devote accordingly in generating an image in their own possible way. To overcome such situation another mechanism i.e. luminosity method was developed. Technical fact about these colors is that the wavelength of red color is more than the wavelengths of green color and the blue color.

The green color provides calming effect to the eyes of the seeker and its wavelength is lesser than the red color. In simple words, the influence of red color has to be reduced and on other hand the green color must be enhanced so that the limit of blue color can be set between red and green. The equation formed for luminosity method is:

$$\text{New Grayscale image} = ((0.3 * R) + (0.59 * G) + (0.11 * B)) \dots\dots\dots (2)$$

Now according to this equation the red color has devoted 33%, the contribution of green color is 59% (which is more than red and blue) and blue has committed only 11% of it.

Step 2: Preprocessing steps: The adaptive filter and the gabor filter have been applied for removing the noise from the image and extracting the useful features from the image respectively.

Step 3: Grayscale Figure Contrast Augment: The technique of contrast augment of images plays a vital role in improving the quality of MRI images and detection of tumor will be lot easier after removing the noisy & brightening up the images. The more clear the image we get it is more easier by the doctor to detect the tumor effected portion in the brain. Imadjust function in the matlab is performed to increase the contrast in the MRI grayscale pictures by creating gamma (γ) transformation. We can brighten up (if $\gamma < 1$) and darken up (if $\gamma > 1$) the images by using the gamma compression. Gamma compression is defined by following terms:

$$V_{out} = AV_{in}^\gamma \dots\dots\dots (3)$$

where A is a constant.

Step 4: Than the picture is cut into four equal parts to calculate max and min pixels and working on parts is more easier way to detect tumor in whole image. Than entropy is applied over it by the algorithm below

$$etp = \frac{-\sum(p * \log_2(p))}{\dots\dots\dots} \dots\dots\dots (4)$$

where p contains the histogram counts returned from imhist.

Than Intensity is adjustment by an image enhancement technique

Step 5: Entropy and intensity of each part is calculated and collected to build up a matrix. The quadrant with maximum intensity is separated out as this is more spectacle of having tumor. After getting that quadrant next step is to work on that quadrant to locate the tumor region in that part.

Step 6: The lower and upper bound threshold is applied to the selective quadrant and calculated temporal values like non linearity, signal dependent and independent noise is derived. Lower bound is derived by average mean-square errors method for any unbiased image restoration scheme. It is expressed analytically as a parameter of degradation of imaging methods. After that calculated values of upper and lower bound threshold is applied onto the selected quadrant.

Step 7: Transformation: Next step is to apply transformations to get tumor portion with highest value of intensity. Two type of transformation is applied i.e. extended maxima transformation, regional maxima transformation. The part with lower pixels will have no chance of having tumor hence neglected and transformations is applied on every part to get highest pixels region

Step 8: Run region properties: We are aware of this fact that we need to know about the properties of a particular connected component (or say object) in order to identify it. In context with this paper, the major task is to detect the tumor present in human brain which is considered as a connected component. Now to verify that whether it's a tumor or not we would apply regionprops command of matlab over that portion to verify its identity. We are also concerned with the solidity (also known as convexity) property of the region. Solidity is the ratio of an area of an object and some other enclosing container. The solidity property of the region specifies the proportion of the pixels which are in the region also in the convex hull. This property supports only 2-D input label matrices. It could be computed as area or convex area. Solidity is bit tough, but probably a good distinguisher of cells with projections or uneven shape v/s round cells generally within the region (intensity and entropy are also high).

Step 9: Mark the boundary around the area which matches to the max profile: Under this step the boundary around detected tumor portion is been built up so that the tumor could be clearly visible and differentiated by the viewer.

Step 10: Count the pixels that lie within the boundary: Finally the tumor portion has been detected and demarcated and now it has to be quantified by counting the no. of pixels that lies within that bordered portion which specifies tumor area.

RESULTS AND ANALYSIS:

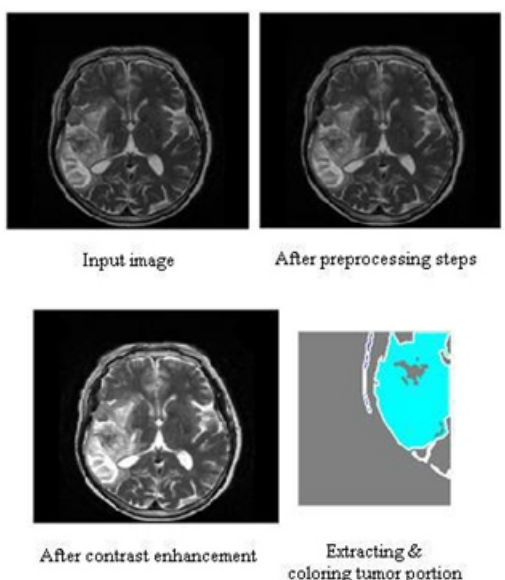


Image name	Image size	Tumor size (in pixels)	Execution time (in sec)
brainimg1	200 X 200	62002	2.342
brainimg2	200 X 200	262145	3.099
brainimg3	200 X 200	66565	2.477
brainimg4	200 X 200	122501	2.984
brainimg5	200 X 200	50626	2.109

RESULTS OF 5 DIFFERENT CASES: CONCLUSION AND FUTURE SCOPE:

After looking into the results it could be said that the proposed method is better than the previous one as it has been found that the execution time has been reduced. Moreover rather than looking into the whole image for the pixels showing tumor the proposed algorithm is searching in just the quadrant where the possibility is highest by using entropy, intensity and solidity matrix and transforming the image. This way the computation also has been lessening up. For future scope, it could be suggested that one can take advantage of machine learning non-parameterized algorithms that uses regression decision tree to arrive at the classification of objects like tumor and non-tumor parts.

REFERENCES:

- [1] Nobuyuki Otsu, "A Threshold Selection Method from Gray-Level Histograms", IEEE Transactions on systems, Man, and Cybernetics, Vol. SMC-9, No. 1, January 1979.
- [2] Michael R. Kaus, Simon K. Warfield, Arya Nabavi, Peter M. Black, Ferenc A. Jolesz, Ron Kikinis, "Automated Segmentation of MR Images of Brain Tumors" Radiology; 218:586-591, Magnetic resonance (MR), Volume measurement, 10.121412, 10.12143, 2001.
- [3] Lynn M. Fletcher-Heath, Lawrence O. Halla, Dmitry B. Goldgof, F. Reed Murtagh, "Automatic segmentation of non-enhancing brain tumors in magnetic resonance images" Artificial Intelligence in Medicine 21: 43-63, Elsevier Science B.V., 2001.
- [4] Alain Pitiot, A.W. Toga, P.M. Thompson, "Adaptive elastic segmentation of brain MRI via shape-model-guided evolutionary programming" IEEE Transactions on Medical Imaging, Vol.: 21, Issue: 8, Aug. 2002.
- [5] Lynn M. Fletcher-Heath, Lawrence O. Halla, Dmitry B. Goldgof, F. Reed Murtagh, "Automatic segmentation of non-enhancing brain tumors in magnetic resonance images" Artificial Intelligence in Medicine 21: 43-63, Elsevier Science B.V., 2001.
- [6] Alain Pitiot, A.W. Toga, P.M. Thompson, "Adaptive elastic segmentation of brain MRI via shape-model-guided evolutionary programming" IEEE Transactions on Medical Imaging, Vol.: 21, Issue: 8, Aug. 2002.
- [7] Yuri Boykov, Vladimir Kolmogorov, "An Experimental Comparison of Min-Cut/Max-Flow Algorithms for Energy Minimization in Vision" IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 26, No. 9, September 2004.
- [8] Stuart S. C. Burnett, George Starkschall, Craig W. Stevens, Zhongxing Liao, "A deformable-model approach to semi-automatic segmentation of CT images demonstrated by application to the spinal canal" The International Journal of Medical Physics Research and Practice, Medical Physics 31, 251 (2004), 22 January 2004.
- [9] Weibei Dou, Su Ruan, Yanping Chen, Daniel Bloyet, Jean-Marc Constans, "A framework of fuzzy information fusion for the segmentation of brain tumor tissues on MR images" Elsevier B.V., Vol. 25, Issue 2, 2006.

[10]Kyungsuk (Peter) Pyun, Johan Lim, Chee Sun Won, Robert M. Gray, "Image Segmentation Using Hidden Markov Gauss Mixture Models" IEEE Transactions on Image Processing, Vol. 16, No. 7, July 2007.

[11]Hassan Khotanlou, Olivier Colliot, Isabelle Bloch "Automatic brain tumor segmentation using symmetry analysis and deformable models" Bu Ali Sina University and Paristechile de France, 2008.

[12]Jason J. Corso, Eitan Sharon, ShishirDube, Suzie El- Saden, UshaSinha, Alan Yuille, "Efficient Multilevel Brain Tumor Segmentation With Integrated Bayesian Model Classification" IEEE Transactions on Medical Imaging, Vol. 27, No. 5, May 2008.

[13]T. Logeswari, M. Karnan, "An improved implementation of brain tumor detection using segmentation based on soft computing" Journal of Cancer Research and Experimental Oncology Vol. 2(1) pp. 006-014, March, 2010.

[14] Sufyan Y. Ababneh, Jeff W. Prescott, Metin N. Gurcan, "Automatic graph-cut based segmentation of bones from knee magnetic resonance images for osteoarthritis research" Elsevier B.V., Vol. 15, Issue 4, August 2011.

[15]P. Narendran, Mr. V.K. Narendira Kumar, Dr. K. Somasundaram, "3D Brain Tumors and Internal Brain Structures Segmentation in MR Images" I.J. Image, Graphics and Signal Processing, 1, 35-43, February 2012.

[16]Sudipta Roy, Samir K. Bandyopadhyay "Detection and Quantification of Brain Tumor from MRI of Brain and it's Symmetric Analysis" International Journal of Information and Communication Technology Research, Vol. 2 No. 6, June 2012.

[17]Mukesh Kumar, Kamal K.Mehta "A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method" International Journal of Computer Technology and Applications, Vol 2 (4), 855-859, August 2011.

[18]Ngah, U. K., Ooi, T. H., Sulaiman, S. N. & Venkatachalam, P. A. (2002). Embedded Enhancement Image Processing Techniques on A Demarcated Seed Based Grown Region. Proc. of Kuala Lumpur Int. Conf. on Bio-medical Engineering. 170-172.

[19]Lim, E. E., Venkatachalam, P. A., Ngah, U. K. & Khalid, N. E. A. (1999). "Liver Disease Diagnosis by Region Growing". Proceedings of International Conference on Robotics, Vision and Parallel Processing for Automation. 1. 38-45.

[20]Khalid, N. E. A., Venkatachalam, P. A. & Ngah, U. K. (1999). "Diagnosis of Bone Lesion Based on Histogram Equalization". Proceedings of International Conference on Robotics, Vision and Parallel Processing for Automation. 1. 91-96.