Mathematical Image Processing For Brain Tumor Identification Using Pixel Set Theory Clustering Technique

Rahul Khalate, Dr. Vineeta Basotia, Dr. Dilip.B.Ghule

Abstract: The mathematical applications are building pillars of engineering and sciences applications. In the era of artificial intelligence, computations are based on mathematical developments. The trust areas for such applications are medical imaging, agricultural internet of things, logistics and space research. As human life is most important element, in this paper we presenting the medical imaging application developed with mathematical modeling using game theory strategy and set theory. The pixel calculations is an important base for medical image study hence, this paper presents new development of research methodology using pixel sets. The brain tumor of type LGG and HGG are modeled with pixel geometrical focus. The proposed research is proved to be important for future medical imaging.

Index Terms: Brain MRI, Fourier transforms, game theory, Laplace pyramid, mathematical application, set theory, tumor detection

1. INTRODUCTION

THE tumor is basically an uncontrolled growth of cancerous cells in any part of the body, whereas a brain tumor is an uncontrolled growth of cancerous cells in the brain [1]. A brain tumor can be benign or malignant. The benign brain tumor [2],[3],[4] has uniformity in structure and does not contain active (cancer) cells, whereas malignant brain tumors have a non-uniformity (heterogeneous) in structure and contain active cells [5],[6]. The gliomas and meningiomas are the examples of low-grade tumors, classified as benign tumors and glioblastoma and astrocytomas are a class of high-grade tumors, classified as malignant tumors [7],[8]. To detect infected tumor tissues from medical imaging modalities, segmentation is employed. Segmentation is necessary and important step in image analysis; it is a process of separating an image into different regions or blocks sharing common and identical properties, such as color, texture, contrast, brightness, boundaries, and gray level [9],[10],[11]. The primary task of preprocessing is to improve the quality of the MR images and make it in a form suited for further processing by human or machine vision system [12]. Preprocessing helps to improve certain parameters of MR images such as; improving the signal to noise ratio [13], enhancing the visual appearance of MR image, removing the irrelevant noise and undesired parts in the background, smoothing the inner part of the region, and preserving its edges [14]. To improve the signal-to-noise ratio, and thus the clarity of the raw MR images, we applied adaptive contrast enhancement based on modified sigmoid function. Many image processing tasks can be formulated as an inverse problem, in which the data f is assumed to be obtained approximately by applying a linear operator A on an image u with additive noise. For example, A is the identity matrix for image de-noising, a convolution matrix for de-blurring, and sub-sampling of Fourier transform for a magnetic resonance imaging (MRI) reconstruction problem [15]. In most scenarios, solving u from $Au = f$ is ill-posed in the sense that directly inverting A would result in bad and possibly multiple solutions [16]. It is necessary and even desirable to constrain the solutions through regularization, with the help of prior knowledge of images that one wants to reconstruct. Minimization methods based on the explicit formula for the gradient allow us to propose efficient numerical algorithms for the approximate solution of inverse problems of wave tomography. The gradient method has regularizing properties and stops when the value of the residual functional becomes equal to the error of the input data [17]. Some of other mathematical modeling can be used as Fourier transform, Laplace pyramid to calculate the covariance function but disadvantage is these methods increases the computational time. Hence, to avoid such demerits, we proposed game theory approach, which focuses on pixel (of brain MR image) set clustering and it can be a good application of applied mathematics with more accuracy and less execution time.

2 EXISTING RESEARCH

Inspired by the latest achievement of convolution neural networks, a growing quantity of deep learning centered automated segmentation algorithms have already been suggested. Existing study runs on the multi-scale architecture by merging features from paths with different filter sizes. They furthermore improved their outcomes by cascading down their versions. Additional author piled more convolution layers with smaller sized (3x3) filter sizes. They develop individual networks for segmentation of LGG and HGG [18]. In short, a Gaussian [19],[20],[21] procedure may be used to produce prophecies regarding most continuous function f(x) provides training data with a set of (x, y) pairs without specifying a elemental type for f(x) with assumption of a function k(x, x_0) which provides the variance of the function elements for any pair x and x_0 . The function of k(x, x_0) is generally become the function f(x) which changes gradually with change in x. Particularly for influence MRI statistics author most recently recommended a covariance function which usually blend a “circular” covariance process for the slanted path and so a square-shaped exponential through the x-value path [22].

3 RESEARCH METHODOLOGY

Quantitative evaluation of mind tumors provides useful info and consequently comprises an important component of analysis methods. Automated segmentation is usually appealing in this framework, as it enables for faster, more goal and possibly more accurate explanation of relevant growth guidelines, like the quantity of its sub regions. Because of to the irregular character of tumors, nevertheless, the advancement of algorithms able of automated segmentation continues to be difficult. The majority of existing methods resolve the over optimization issue with numerous fidelity terms and frequency conditions in either constant or under the radar configurations. Many strategies examine the sparsity of the gradient vectors Du of the outcomes acquired in the de-noising and de-blurring tests. Determine a gradient vector to become non-sparse if both D_{xu} and D_{vu}at that pixel are bigger than 0.001. After that one can determine the percentage of nonsparse gradient vectors over the total quantity of pixels. Additional existing method is usually Laplacian Pyramid Network (LPN) centered on a cascade of convolution neural networks (CNNs).

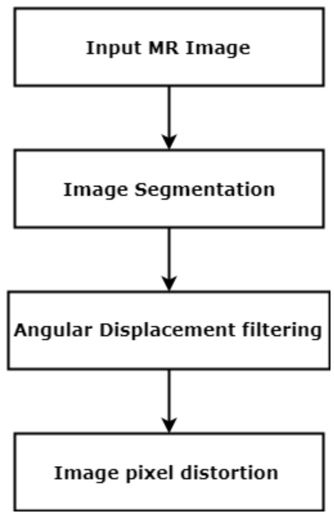

***Fig. 1**. Proposed image processing steps*

Picture based growth phenotyping and produced medically relevant guidelines this kind of as predicted survival is usually typically carried out by means of radiomics. Strength, form and consistency features are therefore calculated from segmentation face masks of the tumor sub regions and consequently utilized to teach a machine learning formula. These features may also become accompanied by additional steps hand made to the issue at hands, like the range of the growth to the ventricles and crucial constructions in the mind. Although our primary concentrate was place on the segmentation component of the problem, we created a basic radiomics centered strategy mixed with an arbitrary forest repressor and a multilayer perception outfit for success conjecture. The proposed methodology is focused on the pixel distortion identification and correction using game theory and set theory pixel clustering. As shown in fig. 1 above, the input is Magnetic Resonance (MR) Image.

- Image Segmentation

Data preprocessing With MRI intensity ideals becoming non standard, normalization is definitely crucial to enable for data from different institutes, scanners and obtained with different protocols to become prepared by one solitary formula. This can be especially accurate for neural networks where imaging strategies are typically treated as color stations.

- Angular Displacement filtering

For oblique angle modification, what matters is usually the oblique position between the scanner and image coordinates. Scanner coordinates send to the coordinates of the MRI scanning device and picture coordinates relates to the coordinates of the Mister pictures.

- Image pixel distortion

Signal loss influencing an entire slice, or a big linked area of a slice, is certainly regularly noticed in diffusion weighted pictures, leading to an arranged of useless measurements. This is triggered by bulk movement during the diffusion development component of the imaging series. We recommend a technique to identify pixels affected by transmission loss and change them by a nonparametric conjecture, in order to reduce their effect on following evaluation. Signal dropout is usually a possibly severe issue that can trigger fake advantages when evaluating organizations where topics in one group are more probably to possess relocated or when regression data against an element that is definitely related with the degree of subject matter motion.When a dropout offers been discovered the following question is usually what to perform about it. One choice would end up being to dispose of the detected slice, but there are some useful complications connected with that. The end result of the corrections is usually a dataset in a solitary space which implies that all of the person diffusion weighted pictures will have got been resample into that space. Therefore a discarded slice will right now be a discarded oblique aircraft with ambiguous edges, and for which one would have required the info from the discarded slice for the interpolation. For mathematical computation, we considered pixel plane process as shown in fig. 2 below.

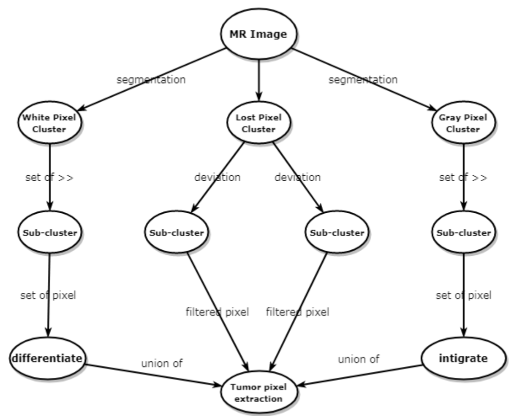

***Fig. 2.** Representation of pixel plane process*

Using set theory cluster extraction approach as a result extracted tumor boundary is noted for tumor type HGG or LGG. The input image is fitted and processed as a plane of pixel coordinates (x, y).

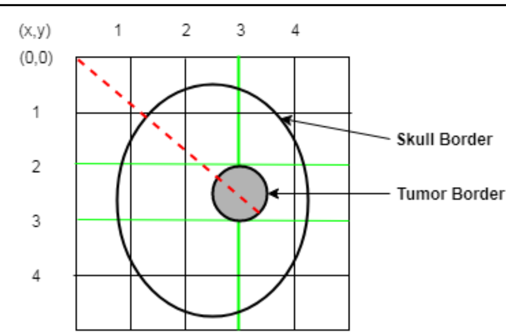

***Fig. 3**. LGG Pixel mapping for pixel set*

As shown in fig. 3 above, we considered LGG brain tumor for pixel mapping using diagonal coordinates (x, y). As shown by red color dotted line, the pixels set is prepared till diagonal end of tumor (gray area) and skull border considered as a plane boundary.

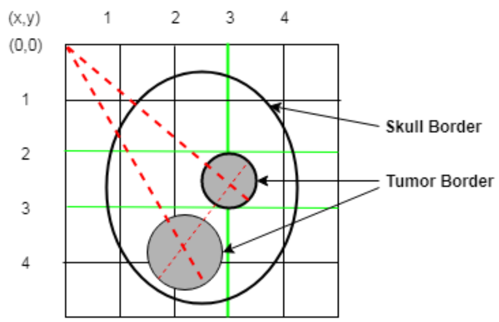

Fig. 4. *HGG Pixel mapping for pixel set*

Similarly, in case of multiple tumors i.e. HGG type tumor, as shown in fig. 4, the set of pixel are considered for diagonal as well as between tumor pixels set for identification of total set of pixels.

4 RESULT AND ANALYSIS

As a set theory cluster formation of pixel is done using game theory pixel travel strategy, the results proved that proposed research is better than any previous mathematical modeling application. The comparative results of machine learning mathematical approaches are shown in following Table 1.

Table 1: *Comparative Performance Analysis*

Sr. No.	Technique used	Visibility (%)	Sensitivity (%)	Execution Time(ms)
1	Proposed Research-Pixel Set Theory	98.16	91.38	45
2	Support Vector Machine	96.56	90.12	48
3	K-Nearest Neighbor	93.40	88.47	46

As a comparative performance representation, following fig. 5 shows that proposed method is performs well as compared to existing SVM and KNN methods for mathematical execution.

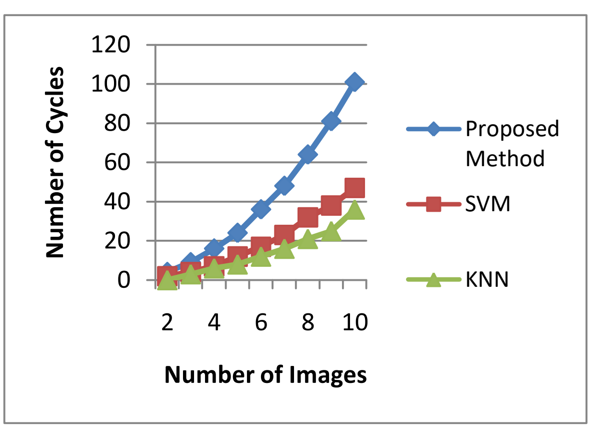

Fig. 5. *Comparative Analysis Chart*

As per comparative analysis shown above, it is clear that the proposed method, pixel set theory is more accurate in terms of visibility, sensitivity and requires moderate execution time.

5 CONCLUSION

We remark that edge detection becomes an important task in our method, since we will not know where the true edges are before we proceed. We presented the pixel set theory mathematical application for medical imaging segment. This method is best suited for surgical analysis of brain tumor. As the visibility is important element for doctors, it is better in case of proposed mathematical application. This research can further be developed as a hardware interfacing tool patch for radiological instrument. The artificial intelligence enabled mathematical application will rule the world in coming era.

ACKNOWLEDGMENT

I wish to thank Dr. Anup Kale, Sydney University for valuable suggestions for mathematical modeling and Dr. Ghule for continuous monitoring of research. Also, I am thankful to my institution for continuous encouragement towards my research. This work was supported in part by a technical laboratory facility provision from Indian Institute for Advanced R&D, IIARD research, Pune.

REFERENCES

[1] Lou, Yifei, et al. "A weighted difference of anisotropic and isotropic total variation model for image processing." SIAM Journal on Imaging Sciences 8.3 (2015): 1798-1823.

[2] Osher, Stanley, Zuoqiang Shi, and Wei Zhu. "Low dimensional manifold model for image processing." SIAM Journal on Imaging Sciences 10.4 (2017): 1669-1690.

[3] Elmoataz, Abderrahim, Matthieu Toutain, and Daniel Tenbrinck. "On the p-Laplacian and ∞-Laplacian on graphs with applications in image and data processing." SIAM Journal on Imaging Sciences 8.4 (2015): 2412-2451.

[4] Awad, Ali Ismail, and Mahmoud Hassaballah. "Image feature detectors and descriptors." Studies in Computational Intelligence. Springer International Publishing, Cham (2016).

[5] Chen, Huasong, et al. "Split Bregmanized anisotropic total variation model for image deblurring." Journal of Visual Communication and Image Representation 31 (2015): 282-293.

[6] Legland, David, Ignacio Arganda-Carreras, and Philippe Andrey. "MorphoLibJ: integrated library and plugins for mathematical morphology with ImageJ." Bioinformatics 32.22 (2016): 3532-3534.

[7] GeethaRamani, R., and Lakshmi Balasubramanian. "Retinal blood vessel segmentation employing image processing and data mining techniques for computerized retinal image analysis." Biocybernetics and Biomedical Engineering 36.1 (2016): 102-118.

[8] Kalavathi, P., and VB Surya Prasath. "Methods on skull stripping of MRI head scan images—a review." Journal of digital imaging 29.3 (2016): 365-379.

[9] Benson, C. C., et al. "Brain tumor segmentation from MR brain images using improved fuzzy c-means clustering and watershed algorithm." 2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI). IEEE, 2016.

[10] Firoz, Raihan, et al. "Medical image enhancement using

morphological transformation." Journal of Data Analysis and Information Processing 4.01 (2016): 1.
[11] Bhima, K., and A. Jagan. "Analysis of MRI based brain tumor identification using segmentation technique." 2016 International Conference on Communication and Signal Processing (ICCSP). IEEE, 2016.
[12] Anitha, V., and S. Murugavalli. "Brain tumour classification using two-tier classifier with adaptive segmentation technique." IET computer vision 10.1 (2016): 9-17.
[13] Devkota, B., et al. "Image segmentation for early stage brain tumor detection using mathematical morphological reconstruction." Procedia Computer Science 125 (2018): 115-123.
[14] Ghamisi, Pedram, et al. "New frontiers in spectral-spatial hyperspectral image classification: The latest advances based on mathematical morphology, Markov random fields, segmentation, sparse representation, and deep learning." IEEE Geoscience and Remote Sensing Magazine 6.3 (2018): 10-43.
[15] Srinivasan, Kavitha, and Nanditha Muthu. "A Comparative Study and Analysis of Contrast Enhancement Algorithms for MRI Brain Image Sequences." 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT). IEEE, 2018.
[16] Sumathi, R., M. Venkatesulu, and Sridhar P. Arjunan. "Extracting tumor in MR brain and breast image with Kapur’s entropy based Cuckoo Search Optimization and morphological reconstruction filters." Biocybernetics and Biomedical Engineering 38.4 (2018): 918-930.
[17] Zhao, Huimin, et al. "Study on a novel fault damage degree identification method using high-order differential mathematical morphology gradient spectrum entropy." Entropy20.9 (2018): 682.
[18] Wang, Pingxin, and Yiyu Yao. "CE3: a three-way clustering method based on mathematical morphology." Knowledge-Based Systems 155 (2018): 54-65.
[19] Hao, Ying, et al. "A novel clustering algorithm based on mathematical morphology for wind power generation prediction." Renewable energy 136 (2019): 572-585.
[20] Xiao, Yiyong, et al. "Optimal mathematical programming and variable neighborhood search for k-modes categorical data clustering." Pattern Recognition 90 (2019): 183-195.
[21] Liu, Luyang, et al. "SAR image change detection based on mathematical morphology and the K-means clustering algorithm." IEEE Access 7 (2019): 43970-43978.
[22] obashi, Yoshinori, Shizuo Kaji, and Kei Iwasaki, eds. Mathematical Insights Into Advanced Computer Graphics Techniques. Springer Singapore, 2019.