AUTOMATIC BRAIN TUMOR SEGMENTATION METHOD USING IMPROVED FUZZY C-MEANS AND FUZZY PARTICLE SWARM OPTIMIZATION

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I dedicate this thesis to the
biggest treasures of my life, my beloved
parents, **Fatemeh** and **Hasan**, and to the best
sister and brother in the world, Najmeh and
Mohammad, and also to my friends and
family for their endless support and
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ABSTRACT

The brain is the most important organ of the human body. It has a complicated structure, and a precise segmentation of brain cerebral tissues plays an important role for tumor detection. Since the manual segmentation is tedious and time-consuming, automatic segmentation becomes a more attractive subject to most researchers. Recently, many automatic segmentation methods have been proposed using clustering algorithms. Nonetheless, there are some remaining issues: noisy images and local optima. This study proposes a hybrid method by combining two clustering methods: FCM-FPSO and IFCM-PSO. In this research, a Gaussian filter is first applied as a pre-processing step to remove noises. Then, the enhanced image is segmented using a modified clustering method called Improved Fuzzy C-Means (IFCM). In IFCM, besides the target pixel intensity, the distance and intensity of the neighbours of the target pixel are used as the segmentation parameters. The presence of these parameters are helpful in case of the segmentation of noisy images. In order to prevent IFCM from falling into local optima, Fuzzy Particle Swarm Optimization (FPSO) is used to improve the parameter initialization step. FPSO is initialized by using a random membership function. The hybrid method is applied on thirty-one MRI brain tumor images collected from MICCAI 2012. The experimental results revealed that the F1-Measure of 79.98%, obtained by proposed hybrid method, is higher than that of the recent segmentation methods.

ABSTRAK

Otak adalah organ yang paling penting dalam tubuh manusia. Ia mempunyai struktur yang rumit, dan segmentasi tepat otak tisu serebral memainkan peranan yang penting untuk mengesan tumor. Segmentasi manual adalah sangat rumit serta memakan masa oleh yang demikian, segmentasi automatik menjadi subjek lebih menarik kepada kebanyakan penyelidik. Baru-baru ini, terdapat banyak kaedah segmentasi automatik dicadangkan menggunakan algoritma kelompok. Walaupun begitu, terdapat beberapa isu yang tertinggal diantaranya adalah seperti; kekaburan imej dan optima tempatan. Kajian ini mencadangkan kaedah hibrid dimana ianya adalah menerusi gabungan dua kaedah berkelompok, iaitu *FCM-FPSO* dan *IFCM-PSO*. Menerusi kajian ini, penapis *Gaussian* akan digunakan sebagai langkah awal untuk menghapuskan hingar. Seterusnya, imej baru yang telah diperbaiki dibahagikan dengan menggunakan kaedah kelompok diubahsuai atau lebih dikenali sebagai *Improved Fuzzy C-Means (IFCM).* Dalam *IFCM,* selain keamatan sasaran piksel, jarak dan intensiti piksel jiranan sasaran digunakan sebagai parameter segmentasi. Kehadiran parameter ini adalah membantu dalam kes segmentasi imej hingar. Dalam usaha untuk mencegah *IFCM* daripada menjadi optima tempatan, *Fuzzy Particle Swarm Optimization (FPSO)* digunakan untuk meningkatkan langkah parameter pengawalan. *FPSO* adalah dimulakan dengan menggunakan fungsi keahlian rawak. Kaedah hibrid digunakan pada tiga puluh satu imej *MRI* otak bertumor yang diambil daripada *MICCAI 2012*. Menerusi kaedah yang dicadangkan, Keputusan eksperimen menunjukkan bahawa *F1-Measure* menghasilkan nilai yang lebih tinggi iaitu 79.98%, dan ianya adalah lebih tinggi daripada kaedah segmentasi terkini.

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LIST OF ABBREVIATIONS

2D	2-Dimensional
3D	3-Dimensional
ANN	Artificial Neural Network
BCFCM	Bias-Corrected Fuzzy C-Means
Centroid	Center of Cluster
CSF	Cerebrospinal Fluid
CT	Computed Tomography
DCE	Discrete Curve Evolution
EnFCM	Enhanced Fuzzy C-Means
FCM	Fuzzy C-Means
FGFCM	Fast Generalized Fuzzy C-Means
FLAIR	Fluid Attenuated Inversion Recovery
FN	False Negative
FP	False Positive
FPSO	Fuzzy Particle Swarm Optimization
GA	Genetic Algorithm
gbest	Global Best Position
GBM	Glioblastoma
GM	Gray Matter
GUI	Graphical User Interface
HG	High-Grade Glioma
HPSO	Hybridized Particle Swarm Optimization
IFCM	Improved Fuzzy C-Means
LG	Low-Grade Glioma
MRI	Magnetic Resonance Image
MRGM	Modified Region Growing Method

NMR	Nuclear Magnetic Resonance
pbest	Personal Best Position
PD	Proton Density
PET	Positron Emission Tomography
PSO	Particle Swarm Optimization
SPECT	Single-Photon Emission Computed Tomography
T1	T1-Weighted
T2	T2-Weighted
TN	True Negative
TP	True Positive
WHO	World Health Organization
WM	White Matter

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CHAPTER 1

INTRODUCTION

1.1 Overview

Image processing is composed of numerous program areas such as compression, enhancement, detection, feature extraction, restoration, scaling, segmentation, and so on. Image segmentation is used in many applications like medical imaging, locating objects in satellite images, face recognition, traffic control systems, and fingerprint recognition. With the latest improvement in medical imaging experiments, the medical images are going to be one of the most reliable standards in the case of diagnosis, treatment planning and evaluation of the diseases. Medical imaging includes locating tumors and other pathologies, measuring tissue volumes, etc.

Magnetic Resonance Image (MRI) generally is a strong, robust and yet an influential visualization system for allowing the images of internal anatomy to be developed in a least interferences and harmless approach (Brown and Semelka, 2011). In specialized medical training, MRI is utilized to tell apart pathologic tissue via regular tissue, specifically for brain related disorders. The MRI brain tumor segmentation is really an essential procedure for medical treatment, monitoring of therapy, efficacy validation of radiation and drug treatments, and revising the variances between healthy and unhealthy subjects (tumors). Specifically in brain tumors, the act of segmenting involves splitting regular brain tissues for instance gray matter, white matter and cerebrospinal fluid from abnormal tissues like active tumors, edema, and also Glioma.

Automated MRI brain tumor segmentation is a complicated challenge especially when it’s along with depreciating factors such as intensity inhomogeneity and noise (Sikka *et al.*, 2009). Partial volume effect, intensity inhomogeneity and noise provide a complex challenging task for MRI brain tumor segmentation. Most of the current segmentation techniques emphasis on only one or two of these artifacts. In case of emergency problems and some critical medical situations, an increased care has been paid on brain tumor segmentation leading to deliver more accuracy in tumor detection value and also to reduce the execution and calculation time of the segmentation in MRI images. This chapter contains a brief introduction to the problem in automatic brain tumor segmentation and methods that worked on it. Afterward, the questions, objectives and scope of the study will be discussed.

1.2 Background of the Study

Presence of lesions or tumors in brain cortex is a critical problem in medical treatment field. In case of this problem, the need of detecting tumors and lesions in medical images is most important concern and make of using a robust and fast algorithm to detect these inhomogeneity is more considerable topic. In this regard many detection algorithms have been proposed and these methods will be discussed in literature review. Most of the existing methods are operative and effective but they have weaknesses in their results. It’s so important to consider that MRI brain tumor segmentation in a fast, robust and accurate method is the challenging issue.

A wide range of brain tumor segmentation methods have already been suggested. Nevertheless, generally there is absolutely no regular segmentation method which may generate acceptable outcomes with regard to almost all image resolution programs. Very frequently, techniques tend to be improved in order to provide with particular the image techniques like MRI. In common, segmentation methods are separated into several main categories (Pham *et al.*, 2000; Farag *et al.*, 2005):

- Methods based on thresholding
- Methods based on region of interest
- Methods based on clustering, and
- Model-based Methods

Nabavi *et al.* (2001) applied a region growing method with regard to segmentation of brain tumor MRI images. The proposed method included the technology of statistical classification in order to discrete the image into diverse classes of tissues on the base of the signal intensity value. Lakare and Kaufman (2000) released the Modified Region Growing Method (MRGM) that is using to be able to eliminate the partial volume effect as well as to include gradient info for much more precise border recognition and stuffing holes happened right after segmentation. Watershed programs have been extensively utilized within brain tumor segmentation. Dam *et al.* (2004) carried out segmentation by making use of multi-scale watershed transformation. They introduced an interactive technique with regard to T1-MRI brain tumor segmentation.

Another sort of segmentation technique is actually dependent on clustering techniques. Pixel classification is usually dependent on gray level images, and the act of segmentation may be carried out within a one-dimensional feature space. Wu *et al.* (2007) has proposed a color-based technique for MR brain images using K-Means algorithm to find the tumor pixels in the images. After converting the gray image to a color image, they have used K-Means clustering and histogram-clustering in order to distinguish normal brain tissues from tumor tissues. Ain *et al.* (2010) has proposed a robust system for brain tumor diagnosis as well as for brain tumor region extraction. Initially, the proposed method has used Bayes classification to identify the tumor from the MRI images.

In numerous circumstances, this is not really simple to figure out if perhaps the pixel ought to fit in to the region or not. This particular is due to the fact that the features to figure out homogeneity might not have keen changes at region borders. In order to relieve the scenario that the pixel have to fit in to the region or not, fuzzy set idea can easily be released in to the segmentation procedure. Fuzzy C-Means (FCM) clustering is an well-known method in the image segmentation field based on unsupervised methods by pixel classification, especially in the situation of segmentation of brain tumors (Supot *et al.*, 2007).

Szilagyi *et al.* (2003) suggested a new method for segmentation of MRI brain tumors which starts with original FCM and Bias-Corrected Fuzzy C-Means (BCFCM) algorithm. The proposed method delivers segmented brain images with enhanced quality in a fast mode. Cai *et al.* (2007) introduced a novel rapid and strong FCM platform for image segmentation: Fast Generalized Fuzzy C-Means (FGFCM) clustering method of integrating local spatial as well as grey information. FGFCM proposed a new feature in the algorithm as a local similarity quantity to assurance both noise-immunity and detail-preserving for image. Shen *et al.* (2005) have proposed an Improved Fuzzy C-Means (IFCM) method to segment MRI brain tissues. To improve the performance of the segmentation, they used a neighborhood attraction, based on the relative location and features of neighboring pixels.

There are many researches based on using PSO as an optimization step to improve clustering algorithms like K-Means and Fuzzy C-Means. The clustering algorithms like FCM are very sensitive to initial parameters. The algorithm may lead to fall into the local optima, if the initial values are not selected properly. To overcome these kind of weaknesses, which results that the FCM algorithm cannot reach the global optimum solution, the using of Particle Swarm Optimization (PSO) as an optimization method has been introduced.

Li and Shen (2010) proposed the FCM clustering method based on Hybridized Particle Swarm Optimization (HPSO). In their study, the PSO is used to find the initial centroids of the clusters. Forouzanfar *et al.* (2010) used Genetic

Algorithms (GA) and PSO to figure out the best value associated with level of attraction. In the study, they mentioned that GAs are finest at getting a close optimum solution however they have problems to discover a strict solution, while PSOs improve the search to find an optimum solution. In another study, Izakian and Abraham (2011) proposed a hybrid fuzzy clustering method called FCM-FPSO. The proposed method improved the merits of both FCM and PSO algorithms by combination of traditional FCM with the Fuzzy PSO algorithm. In the case of noisy MRI images, the efficiency of FCM will be reduced. Forghani *et al.* (2007) presented a method called IFCM-PSO which is using PSO to compute two parameters in order to improve performance of improved FCM (IFCM). Simulation results demonstrated effectiveness of the new proposed in the case of segmentation for noisy MRI images.

In this regard, this thesis focuses on an automated brain tumor detection and segmentation system that improves detection and visualization of brain tumors from Fluid Attenuated Inversion Recovery (FLAIR) images. In terms of the enhancement of the segmentation, this research will focus on an image enhancement process using Gaussian Filter. To achieve that goal, improved Fuzzy C-Means algorithm will be used in order to find better FCM initial parameters, such as membership function matrix and center of cluster, an improved intelligent optimization algorithm FPSO will be utilized. In other words, the purpose of this research is to apply a combination of two popular algorithms namely Fuzzy C-Means and PSO to achieve a fast, robust and accurate tumor segmentation.

1.3 Problem Statement

Manual segmentation and analyzing the MR brain tumor images by radiologists is reliable, but with no doubt it is tedious, time-consuming, highly subjective and impractical in today’s medical imaging diagnosis where large numbers of images are taken for a single patient. Thereby, in recent years many efforts have been done to introduce an effective and reliable framework which is useful for automatic brain segmentation but there is still no versatile framework in this field.

As it already discussed in previous section, so many researches have been done in order to making use of FCM to segment the medical images and detecting the location of tumors. Nevertheless, generally there are some problems in these approaches. One of them is that the traditional FCM is usually suffering fall into local optima. So, the problem is preventing FCM to fall into local optima. Another problem in case of noisy images is that, the traditional FCM method is not more efficient. Then, finding a proper way in order to improve the performance and accuracy of the FCM can be a really interesting research area. FCM is not considering intensity of neighborhoods in order to categorizing the pixels into clusters. Another problem is that to propose a better approach in terms of considering number of neighbors to cluster the pixels.

According to this brief description, there are some primary issues considered here:

i. How to increase the accuracy of the system for MRI brain tumor image segmentation in order to considering pixels neighborhood?

ii. How to prevent FCM from falling into local optima using an optimization algorithm?

iii. How efficient is the improved Fuzzy C-Means method with using Fuzzy Particle Swarm Optimization to prepare most valuable and reliable segmentation?

1.4 Research Aim and Objectives

The project aims to examine the use of Fuzzy Particle Swarm Optimization during initializing parameters of improved Fuzzy C-Means clustering algorithm which are the initial fuzzy membership function and subsequently the number of centroids of the defined classes.

This research aims to accomplish these objectives:

i. To hybrid IFCM and FPSO in order to increase the accuracy of brain tumor segmentation.
ii. To validate the results of the method by using “Ground Truth” images that collected from MICCAI 2012.
iii. To evaluate the efficiency of the method in terms of accuracy using F1-Measure parameter.

1.5 Scope of the Study

This project involves the following scope:

i. The hybrid method applied on 31 brain tumor images including 19 real data and 12 simulated data from MICCAI 2012 Challenge on Multimodal Brain Tumor Segmentation (Menze *et al.*, 2012).
ii. Since the images are needed to be enhanced, a pre-processing step will be applied on the images using Gaussian filter.
iii. Improved Fuzzy C-Means method will be used along with an intelligent optimization method Fuzzy PSO in order to accomplish automatic brain tumor segmentation in MRI images.
iv. Since the focus of the research is on increasing the accuracy in FCM clustering algorithm, the execution time evaluation is beyond the study.
v. The performance of the hybrid method in terms of accuracy will be analyzed by comparing the results with two past proposed methods which are IFCM-PSO (Forghani *et al.*, 2007) and FCM-FPSO (Izakian and Abraham, 2011).

vi. The hybrid method will be implemented on windows environment using MatLab 2013b v8.2.

1.6 Significant of the Study

As it already mentioned before, there is still no reliable framework to segment automatically brain tumors from medical images. All the previous studies suffering from increasing the execution time and high average error rate. This research and some other studies related to this subject area are so important because in the scientific organization, whether on medical or computer science, detecting the abnormal lesions or tumors in the human body is the vital concern. Brain tumor detection is also more important than other part of the body. As a result, achieving to an effective, and reliable method to segment and subsequently detect the lesion or tumor position in brain could be hopeful and useful improvement on the medical science industry.

1.7 Thesis Organization

The thesis is prepared into five chapters. The first chapter presents the introduction of the research, background of the study, problem statement, objectives of the study, the aims of the research, scope and the significant of the study. In chapter two, previous and related works on brain tumor segmentation will be discussed. The literature review is about existing techniques for brain tumor segmentation for MRI images. In chapter 3 the research methodology will be explained. The experimental results will be presented and discussed in chapter 4. And finally, conclusions, limitations of the work and future work will be addressed in chapter 5.

REFERENCES

Ahmed, M. M. and D. B. Mohamad, 2008. Segmentation of brain MR images for tumor extraction by combining kmeans clustering and perona-malik anisotropic diffusion model. *International Journal of Image Processing* 2(1): 27-34.

Ain, Q.-u., I. Mehmood, S. M. Naqi and M. A. Jaffar, 2010. Bayesian classification using DCT features for brain tumor detection. *Knowledge-Based and Intelligent Information and Engineering Systems*, Springer: 340-349.

Bezdek, J. C., L. Hall and L. Clarke, 1993. Review of MR image segmentation techniques using pattern recognition. *MEDICAL PHYSICS-LANCASTER PA-* 20: 1033-1033.

Bhattacharya, M. and A. Das, 2008. A study on seeded region based improved watershed transformation for brain tumor segmentation. *The XXIX General Assembly of the International Union of Radio Science*.

Brown, M. A. and R. C. Semelka, 2011. *MRI: basic principles and applications*, John Wiley & Sons.

Buckner, J. C., P. D. Brown, B. P. O'Neill, F. B. Meyer, C. J. Wetmore and J. H. Uhm, 2007. Central nervous system tumors. *Mayo Clinic Proceedings*, Elsevier, 1271-1286.

Cai, W., S. Chen and D. Zhang, 2007. Fast and robust fuzzy< i> c</i>-means clustering algorithms incorporating local information for image segmentation. *Pattern Recognition* 40(3): 825-838.

Chandra, S., R. Bhat and H. Singh, 2009. A PSO based method for detection of brain tumors from MRI. *Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on*, IEEE, 666-671.

Chang, H.-H. and D. J. Valentino, 2008. An electrostatic deformable model for medical image segmentation. *Computerized Medical Imaging and Graphics* 32(1): 22-35.

Dam, E., M. Loog and M. Letteboer, 2004. Integrating automatic and interactive brain tumor segmentation. *Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on*, IEEE, 790-793.

Dou, W., S. Ruan, Y. Chen, D. Bloyet and J.-M. Constans, 2007. A framework of fuzzy information fusion for the segmentation of brain tumor tissues on MR images. *Image and vision Computing* 25(2): 164-171.

Farag, A., M. Ahmed, A. El-Baz and H. Hassan, 2005. Advanced Segmentation Techniques. *Handbook of Biomedical Image Analysis*. J. Suri, D. Wilson and S. Laxminarayan, Springer US**:** 479-533.

Forghani, N., M. Forouzanfar and E. Forouzanfar, 2007. MRI fuzzy segmentation of brain tissue using IFCM algorithm with particle swarm optimization. *Computer and information sciences, 2007. iscis 2007. 22nd international symposium on*, 1-4.

Forouzanfar, M., N. Forghani and M. Teshnehlab, 2010. Parameter optimization of improved fuzzy c-means clustering algorithm for brain MR image segmentation. *Engineering Applications of Artificial Intelligence* 23(2): 160-168.

Gordillo, N., E. Montseny and P. Sobrevilla, 2010. A new fuzzy approach to brain tumor segmentation. *Fuzzy Systems (FUZZ), 2010 IEEE International Conference on*, IEEE, 1-8.

Gordillo, N., E. Montseny and P. Sobrevilla, 2013. State of the art survey on MRI brain tumor segmentation. *Magnetic Resonance Imaging* 31(8): 1426-1438.

Ibrahim, S., N. E. A. Khalid and M. Manaf, 2010. Empirical study of brain segmentation using particle swarm optimization. *Information Retrieval & Knowledge Management,(CAMP), 2010 International Conference on*, IEEE, 235-239.

Izakian, H. and A. Abraham, 2011. Fuzzy C-means and fuzzy swarm for fuzzy clustering problem. *Expert Systems with Applications* 38(3): 1835-1838.

Jiji, G. W. and L. Ganesan, 2005. Unsupervised Segmentation using Fuzzy Logic based Texture Spectrum for MRI Brain Images. *WEC (5)*, 155-157.

Jobin Christ, M. C. and R. M. S. Parvathi, 2012. A Survey on MRI Brain Segmentation. *Advances in Computer Science, Engineering & Applications*. D. C. Wyld, J. Zizka and D. Nagamalai, Springer Berlin Heidelberg. 166**:** 167-177.

Kaur, A. and M. Singh, 2012. An overview of pso-based approaches in image segmentation. *International Journal of Engineering and Technology* 2(8): 1349-1357.

Kennedy, J. F., J. Kennedy and R. C. Eberhart, 2001. *Swarm intelligence*, Morgan Kaufmann.

Lakare, S. and A. Kaufman, 2000. 3D segmentation techniques for medical volumes. *Center for Visual Computing, Department of Computer Science, State University of New York*.

Li, L., X. Liu and M. Xu, 2007. A novel fuzzy clustering based on particle swarm optimization. *Information Technologies and Applications in Education, 2007. ISITAE'07. First IEEE International Symposium on*, IEEE, 88-90.

Li, Y.-l. and Y. Shen, 2010. Fuzzy C-means cluster segmentation algorithm based on hybridized particle swarm optimization. *Bio-Inspired Computing: Theories and Applications (BIC-TA), 2010 IEEE Fifth International Conference on*, IEEE, 811-815.

Louis, D. N., H. Ohgaki, O. D. Wiestler, W. K. Cavenee, P. C. Burger, A. Jouvet, B. W. Scheithauer and P. Kleihues, 2007. The 2007 WHO classification of tumours of the central nervous system. *Acta neuropathologica* 114(2): 97-109.

Menze, B., A. Jakab, S. Bauer, M. Reyes, M. Prastawa and K. Van Leemput, 2012. MICCAI 2012 Challenge on Multimodal Brain Tumor Segmentation.

Nabavi, A., P. M. Black, F. A. Jolesz and R. Kikinis, 2001. Automated segmentation of MR images of brain tumors. *measurement* 10: 10.12143.

Noback, C. R., N. L. Strominger, R. J. Demarest and D. A. Ruggiero, 2005. *The human nervous system: structure and function*, Springer.

Olabarriaga, S. D. and A. W. Smeulders, 2001. Interaction in the segmentation of medical images: A survey. *Medical image analysis* 5(2): 127-142.

Paul, T. U. and S. K. Bandhyopadhyay, 2012. Segmentation of Brain Tumor from Brain MRI Images Reintroducing K–Means with advanced Dual Localization

Method. *International Journal of Engineering Research and Applications (IJERA)* 2(3): 226-231.

Pham, D. L., C. Xu and J. L. Prince, 2000. A survey of current methods in medical image segmentation. *Annual review of biomedical engineering* 2(1): 315-337.

Powers, D. M., 2011. Evaluation: from precision, recall and F-measure to ROC, informedness, markedness & correlation. *Journal of Machine Learning Technologies* 2(1): 37-63.

Prastawa, M., E. Bullitt and G. Gerig, 2009. Simulation of brain tumors in MR images for evaluation of segmentation efficacy. *Medical image analysis* 13(2): 297-311.

Ramathilagam, S., R. Pandiyarajan, A. Sathya, R. Devi and S. Kannan, 2011. Modified fuzzy c-means algorithm for segmentation of T1–T2-weighted brain MRI. *Journal of Computational and Applied Mathematics* 235(6): 1578-1586.

Ratan, R., S. Sharma and S. Sharma, 2009. Multiparameter segmentation and quantization of brain tumor from MRI images. *Indian Journal of Science and Technology* 2(2): 11-15.

Rexilius, J., H. K. Hahn, J. Klein, M. G. Lentschig and H.-O. Peitgen, 2007. Multispectral brain tumor segmentation based on histogram model adaptation. *Medical Imaging*, International Society for Optics and Photonics, 65140V-65140V-65110.

Rodriguez, A., 2009. Principles of magnetic resonance imaging. *Revista mexicana de física* 50(3): 272-286.

Roy, S., S. Nag, I. K. Maitra and S. K. Bandyopadhyay, 2013. A Review on Automated Brain Tumor Detection and Segmentation from MRI of Brain. *arXiv preprint arXiv:1312.6150*.

Runkler, T. A. and C. Katz, 2006. Fuzzy clustering by particle swarm optimization. *Fuzzy Systems, 2006 IEEE International Conference on*, IEEE, 601-608.

Sato, M., S. Lakare, M. Wan, A. Kaufman and M. Nakajima, 2000. A gradient magnitude based region growing algorithm for accurate segmentation. *Image Processing, 2000. Proceedings. 2000 International Conference on*, IEEE, 448-451.

Schmidt, M., 2005. Automatic brain tumor segmentation.

Shen, S., W. Sandham, M. Granat and A. Sterr, 2005. MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization. *Information Technology in Biomedicine, IEEE Transactions on* 9(3): 459-467.

Shi, Y. and R. Eberhart, 1998. A modified particle swarm optimizer. *Evolutionary Computation Proceedings, 1998. IEEE World Congress on Computational Intelligence., The 1998 IEEE International Conference on*, IEEE, 69-73.

Sikka, K., N. Sinha, P. K. Singh and A. K. Mishra, 2009. A fully automated algorithm under modified FCM framework for improved brain MR image segmentation. *Magnetic Resonance Imaging* 27(7): 994-1004.

Stefan, B., W. Roland, P. N. Lutz and R. Mauricio, 2013. A survey of MRI-based medical image analysis for brain tumor studies. *Physics in Medicine and Biology* 58(13): R97.

Supot, S., C. Thanapong, P. Chuchart and S. Manas, 2007. Segmentation of magnetic resonance images using discrete curve evolution and fuzzy clustering. *Integration Technology, 2007. ICIT'07. IEEE International Conference on*, IEEE, 697-700.

Szilagyi, L., Z. Benyo, S. M. Szilágyi and H. Adam, 2003. MR brain image segmentation using an enhanced fuzzy c-means algorithm. *Engineering in Medicine and Biology Society, 2003. Proceedings of the 25th Annual International Conference of the IEEE*, IEEE, 724-726.

Veloz, A., S. Chabert, R. Salas, A. Orellana and J. Vielma, 2007. Fuzzy spatial growing for glioblastoma multiforme segmentation on brain magnetic resonance imaging. *Progress in Pattern Recognition, Image Analysis and Applications*, Springer**:** 861-870.

Vijayakumar, C. and D. C. Gharpure, 2011. Development of image-processing software for automatic segmentation of brain tumors in MR images. *Journal of medical physics/Association of Medical Physicists of India* 36(3): 147.

Wei, P., W. Kang-Ping, Z. Chun-Guang and D. Long-Jiang, 2004. Fuzzy discrete particle swarm optimization for solving traveling salesman problem. *Computer and Information Technology, 2004. CIT '04. The Fourth International Conference on*, 796-800.

Wong, K.-P., 2005. Medical Image Segmentation: Methods and Applications in Functional Imaging. *Handbook of Biomedical Image Analysis*. J. Suri, D. Wilson and S. Laxminarayan, Springer US**:** 111-182.

Wu, M.-N., C.-C. Lin and C.-C. Chang, 2007. Brain tumor detection using color-based k-means clustering segmentation. *Intelligent Information Hiding and Multimedia Signal Processing, 2007. IIHMSP 2007. Third International Conference on*, IEEE, 245-250.

Xie, K., J. Yang, Z. Zhang and Y. Zhu, 2005. Semi-automated brain tumor and edema segmentation using MRI. *European Journal of Radiology* 56(1): 12-19.

Yao, J., 2005. Image processing in tumor imaging. *New techniques in oncologic imaging*: 79.

Zhang, J., K.-K. Ma, M.-H. Er and V. Chong, 2004. Tumor segmentation from magnetic resonance imaging by learning via one-class support vector machine. *International Workshop on Advanced Image Technology (IWAIT'04)*, 207-211.

Zhang, Y., D. Huang, M. Ji and F. Xie, 2011. Image segmentation using PSO and PCM with Mahalanobis distance. *Expert Systems with Applications* 38(7): 9036-9040.