Research Article

Brain Image Segmentation Based on Fuzzy Clustering

Shatha J. Mohammed[1], Mohammed Y. Kamil[2*]
[1]College of Science, Mustansiriyah University, IRAQ.
[2]Departemeent of Physics, College of Science, Mustansiriyah University, IRAQ
*Correspondent Author Email: m80y98@uomustansiriyah.edu.iq

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Abstract

The segmentation performance is topic to suitable initialization and best configuration of supervisory parameters. In medical image segmentation, the segmentation is very important when the diagnosing becomes very hard in medical images which are not properly illuminated.

This paper proposes segmentation of brain tumour image of MRI images based on spatial fuzzy clustering and level set algorithm. After performance evaluation of the proposed algorithm was carried on brain tumour images, the results showed confirm its effectiveness for medical image segmentation, where the brain tumour is detected properly.

Keywords: Brain image, Fuzzy, clustering, level set, Segmentation.

الخلاصة

ان أداء تجزئة الصورة من مواضيع التهيئة المناسبة وافضل ترتيب للمتغيرات الموجهة. في تجزئة الصورة الطبية ، تكون التجزئة جدا مهمة عندما يصبح التشخيص صعبا في الصور الطبية غير المضاءة بشكل صحيح.

تقترح هذه الورقة تقنية تجزئة لورم الدماغ من صور التصوير بالرنين المغناطيسي على أساس العنقدة الغامضة المكانية وخوارزميات مجموعة المستوى. وبعد اجراء تقييم الخوارزمية المقترحة على صور الورم الدماغي ، أظهرت النتائج تأكيد فعالية الخوارزمية في تجزئة الصور الطبية ، حيث يتم اكتشاف ورم الدماغ بشكل صحيح.

Introduction

An initial formulation of level set methods was presented by Malladi *et al.* [1] and Caselles et al.[2]. Level set techniques extract contours as the zero level set of a function formulated in a higher dimension space based on dynamic implied boundaries and partial differential equations (PDEs) [3]. Chan and Vese [4] proposed a level set segmentation method based on an active contour model using the energy minimization method and incorporating region-based information in the energy functional as an extra constraint[5, 6].

As a famous unsupervised clustering technique, fuzzy c-means (FCM) is based on the idea of uncertainty of belonging described by a membership grade that falls between zero to one and has the ability to employ more information from the image in comparison with the crisp or hard segmentation methods[7]. FCM reveals the original structure of the image data and segments it into parts with nearly constant spectral properties[8]. An important disadvantage of FCM is that when it is utilized as a segmentation method in image processing and analysis, topological information and spatial relationship is totally ignored [9-11].

Materials and Methodology

The level set segmentation method was initially proposed to track moving interfaces by Osher and Sethian in 1988 and has spread across various imaging domains in the late 90s. It can be used to efficiently address the problem of curve/surface/etc. propagation in an implicit manner.

The central idea is to represent the evolving contour using a signed function whose zero corresponds to the actual contour. Then, according to the motion equation of the

contour, one can easily derive a similar flow for the implicit surface that when applied to the zero level will reflect the propagation of the contour[12]. The level set method affords numerous advantages: it is implicit, is parameter-free, provides a direct way to estimate the geometric properties of the evolving structure, allows for change of topology, and is intrinsic.[13, 14] It can be used to define an optimization framework, as proposed by Zhao, Merriman and Osher in 1996. One can conclude that it is a very convenient framework for addressing numerous applications of computer vision and medical image analysis[15, 16]. Research into various level set data structures has led to very efficient implementations of this method.[17]

Results and Discussion

The experiments and performance evaluation were carried on medical images from MRI slice of cerebral tissues. Both algorithms of spatial FCM and the proposed fuzzy level set method were implemented with Matlab R2013a in a Windows XP system were run on a Dell computer with CPU 2.4 GHz and 4GB RAM.

The ability of FCM to classify the tissue classes present in the real MR images is qualitatively analyzed. The raw MR image, clustered image for 2 classes are showed in Figure 1.

Figs. 2 and 3 correspond to 5 and 8 classes.it is contain five and eight tissue types and background. The morphological structures present in second and third test images are WM, GM, CSF, necrotic focus and edema. But, CSF is absent in the first test image.

Figure 4 illustrates the more difficult case, which requires the separation of white matter (WM) and gray matter (GM) from an MRI slice of cerebral tissue. It is obvious that WM and GM intertwine with each other and are dispersed over the entire slice, which makes manual initialization nearly impractical.

Figure 5 shows the affect and the number of iteration on segmentation by clustering, which necessitates the separation of (WM) and (GM) from cerebral tissue. In this case we were used the seven classes for FCM and about iteration (100, 200, 300 and 400). It is appearing the increase the iteration, the result is better and clearly.

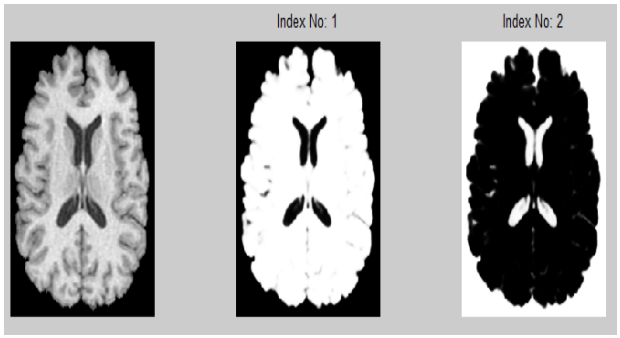

Figure 1: Raw MR clustered by two classes.

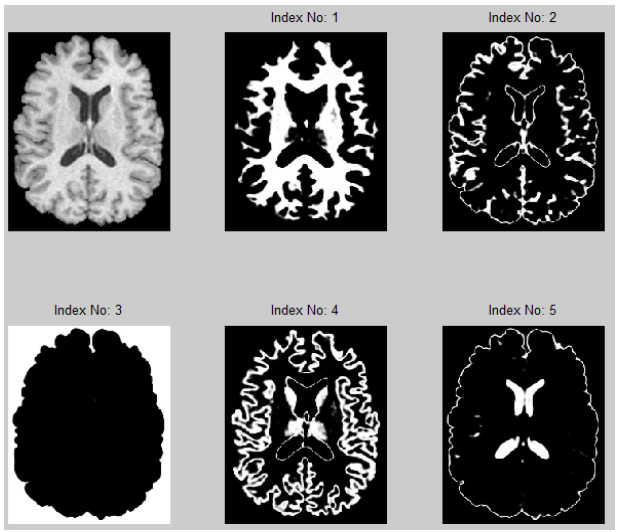

Figure 2: Raw MR clustered by five classes.

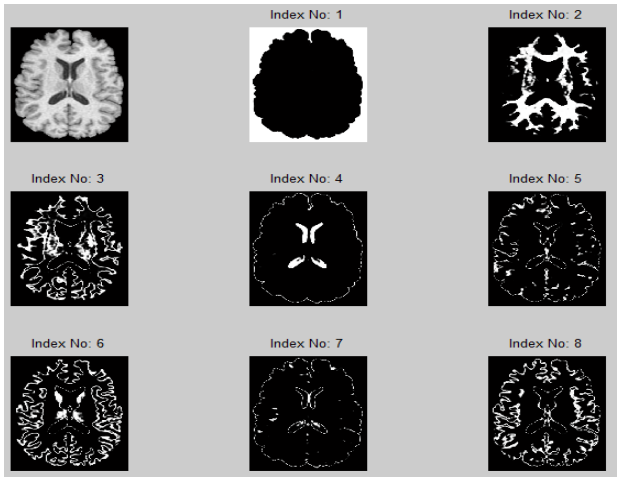

Figure 3: Raw MR clustered by eight classes.

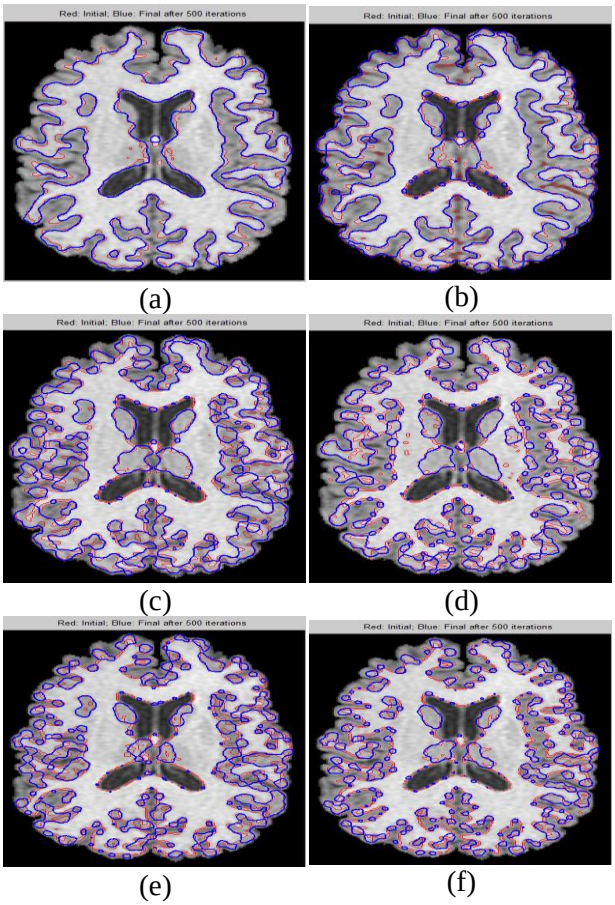

Figure 4: segmentation of MRI brain, final segmentation after 500 iterations, with (a) 3 classes. (b) 4 classes. (c) 5 classes. (d) 6 classes. (e) 7 classes. (f) 8 classes.

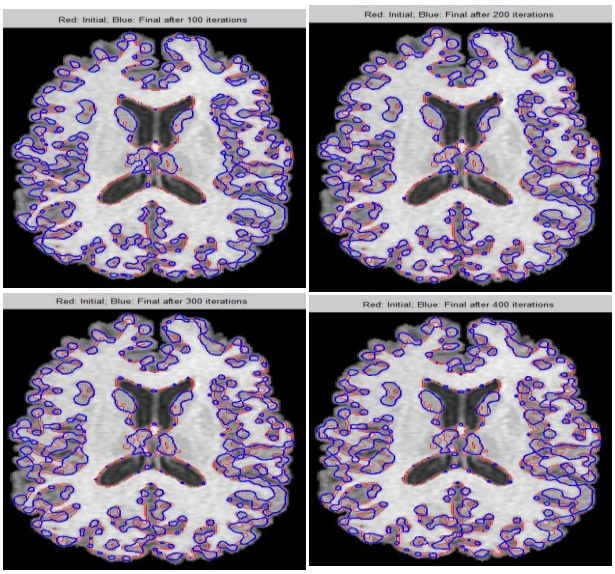

Figure 5: segmentation of MRI brain for different iterations and 7 classes.

Conclusions

The objectives of cluster analysis are to classify objects according to their similarity, and to organize data in totals. The FCM and level set algorithm has been applied to classify the image data set into a number of clusters. The results obtained using MATLAB after the application of this algorithm were compared to a set of brain tissue images of magnetic resonance imaging images obtained from global databases and gave good results to distinguish the brain tissue of the three regions (WM, WG and CSF). Experiments on a benchmark set of brain tumour images show that the proposed algorithm strategy can attain more accurate segmentations.

References

[1] R. Malladi, J. A. Sethian, and B. C. Vemuri, "Shape modeling with front propagation: A level set approach," *IEEE transactions on pattern analysis and machine intelligence*, vol. 17, pp. 158-175, 1995.

[2] V. Caselles, F. Catté, T. Coll, and F. Dibos, "A geometric model for active contours in image processing," *Numerische mathematik*, vol. 66, pp. 1-31, 1993.

[3] S. Osher and J. A. Sethian, "Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations," *Journal of computational physics*, vol. 79, pp. 12-49, 1988.

[4] T. F. Chan and L. A. Vese, "Active contours without edges," *IEEE Transactions on image processing*, vol. 10, pp. 266-277, 2001.

[5] M. Y. Kamil, "Brain Tumor Area Calculation in CT-scan image using Morphological Operations," *IOSR Journal of Computer Engineering*, vol. 17, pp. 125-128, 2015.

[6] S. Madhukumar and N. Santhiyakumari, "Evaluation of k-Means and fuzzy C-means segmentation on MR images of

brain," *The Egyptian Journal of Radiology and Nuclear Medicine*, vol. 46, pp. 475-479, 2015.

[7] A. Liew, S. Leung, and W. Lau, "Fuzzy image clustering incorporating spatial continuity," *IEE Proceedings-Vision, Image and Signal Processing*, vol. 147, pp. 185-192, 2000.

[8] M. Y. Kamil, "Morphological gradient in brain magnetic resonance imaging based on intuitionistic fuzzy approach," in *Multidisciplinary in IT and Communication Science and Applications (AIC-MITCSA), Al-Sadeq International Conference on*, 2016, pp. 1-3.

[9] M. Y. Kamil, "Edge detection for Diabetic Retinopathy using fuzzy logic," *IJS*, vol. 55, pp. 1395-1401, 2014.

[10] M. Y. Kamil, "Hybrid Algorithm for Edge Detection using Fuzzy Inference System," *International Journal of Computer Applications*, vol. 102, 2014.

[11] L. Wang and C. Pan, "Robust level set image segmentation via a local correntropy-based K-means clustering," *Pattern Recognition*, vol. 47, pp. 1917-1925, 2014.

[12] X.-L. Jiang, Q. Wang, B. He, S.-J. Chen, and B.-L. Li, "Robust level set image segmentation algorithm using local correntropy-based fuzzy c-means clustering with spatial constraints," *Neurocomputing*, vol. 207, pp. 22-35, 2016.

[13] P. R. Bai, Q. Y. Liu, L. Li, S. H. Teng, J. Li, and M. Y. Cao, "A novel region-based level set method initialized with mean shift clustering for automated medical image segmentation," *Computers in biology and medicine*, vol. 43, pp. 1827-1832, 2013.

[14] K. Thapaliya, J.-Y. Pyun, C.-S. Park, and G.-R. Kwon, "Level set method with automatic selective local statistics for brain tumor segmentation in MR images," *Computerized Medical Imaging and Graphics*, vol. 37, pp. 522-537, 2013.

[15] A. Gharipour and A. W.-C. Liew, "An integration strategy based on fuzzy clustering and level set method for cell image segmentation," in *Signal Processing, Communication and Computing (ICSPCC), 2013 IEEE International Conference on*, 2013, pp. 1-5.

[16] S. Kannan, R. Devi, S. Ramathilagam, and K. Takezawa, "Effective FCM noise clustering algorithms in medical images," *Computers in biology and medicine*, vol. 43, pp. 73-83, 2013.

[17] H. Masoumi, A. Behrad, M. A. Pourmina, and A. Roosta, "Automatic liver segmentation in MRI images using an iterative watershed algorithm and artificial neural network," *Biomedical Signal Processing and Control*, vol. 7, pp. 429-437, 2012.