ISSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 2, Issue 3, pp: (84-89), Month: July - September 2014, Available at: www.researchpublish.com

# PSNR Based Fuzzy Clustering Algorithms for MRI Medical Image Segmentation

Arthik Daniel[1], S.Anantha Vignesh[2]

[1]Assistant Professor, [2,]UG Scholar
Department of Computer Science and Engineering, Saveetha School of Engineering
Saveetha University, Chennai, Tamil Nadu.

***Abstract**:* **During this paper, the PSNR primarily {based} performances of the assorted fuzzy based algorithms for medical image segmentation are given. The analysis of Fuzzy c-means (FCM) formula in terms of peak signal to noise magnitude relation (PSNR) is given for medical image segmentation. Fuzzy c-means information for medical image segmentation. The formula utilizes the spacial neighborhood membership values within the standard kernels square measure employed in the kernel FCM (KFCM) algorithm and modifies the membership coefficient of every cluster. During this paper, the on the market varied fuzzy algorithms are tested on brain MRI that degraded by Gaussian noise. The performance is tested in terms of PSNR for the agglomeration of images. However, still it lacks in obtaining lustiness to noise and outliers, particularly within the absence of previous information of the noise. To beat this downside, differing kinds of fuzzy algorithms square measure introduced with and while not spacial fuzzy, multiple-kernal.**

***Keywords:*** **FCM, Image Segmentation, membership functions, (FCM) formula has tried its effectiveness for image segmentation.**

## I. INTRODUCTION

Image segmentation is one in all the primary and most vital tasks in image analysis and laptop vision. Within the literature, various ways are planned for object segmentation and feature extraction, represented in [1] and [2]. However, the design of sturdy and economical segmentation algorithms remains a very difficult analysis topic, attributable to the variability and complexity of pictures. Image segmentation is outlined because the partitioning of a picture into non overlapped, consistent regions that square measure homogenised in regard to some characteristics like intensity, color, tone, texture, etc. The image segmentation is often divided into four categories: thresholding, clustering, edge detection and region extraction. During this report, an agglomeration methodology for image segmentation is thought-about. The application of image process techniques has rapidly inflated in recent years. Nowadays, capturing and storing of medical pictures square measure done digitally. Image segmentation is to partition image to totally different regions based mostly on given criteria for future method. Medical image segmentation could be a key task in several medical applications.

There square measure uncountable ways for automatic and semi automatic image segmentation, though, most of them fail in unknown noise, poor image distinction, and weak boundaries that square measure usual in medical pictures. Medical pictures largely contain complicated structures and their precise segmentation is necessary for clinical identification [3].Magnetic resonance imaging (MRI) could be a very hip medical imaging technique, chiefly as a result of its high resolution and distinction that represent nice advantage above different diagnostic imaging modalities. Besides of these good properties, MRI additionally suffers from 3 substantial obstacles: noises (mixture of Gaussian and impulse noises), artifacts, and intensity in homogeneity [4].In recent literatures, many approaches square measure there for medical image segmentation. The on the market segmentation methods in literature for medical pictures are: thresholding approaches, agglomeration approaches, classifiers, region growing approaches, Artificial Neural Networks (ANNs), deformable models; mathematician Random Field (MRF) models atlas-guided approaches so on. Amongst the higher than aforementioned methods, in medical imaging analysis agglomeration based mostly approaches perceived a good focus of interest. Clustering could be a method for classifying objects or patterns in such how that samples of identical cluster square measure a lot of similar to each other than samples happiness to totally different clusters. There square measure 2 main agglomeration strategies: the laborious clustering theme and also the fuzzy agglomeration theme. Forgy and MacQueen [5] planned K-means agglomeration formula. K-means is one in all the laborious agglomeration methodology. The conventional laborious agglomeration ways classify every purpose of the data set simply to at least one cluster. As a consequence, the results are typically terribly crisp, i.e., in image agglomeration every picture element of the image belongs simply to at least one cluster. However, in several real situations, problems like restricted spacial resolution, poor contrast, overlapping intensities, noise and intensity in homogeneities cut back the effectiveness of laborious (crisp) clustering ways. Fuzzy pure mathematics [7] has introduced the idea of partial membership, represented by a membership function. Fuzzy agglomeration, as a soft segmentation methodology, has been wide studied and with success applied in image clustering and segmentation [8]–[13]. Among the fuzzy clustering ways, fuzzy c-means (FCM) formula [14] is the most standard methodology employed in image segmentation because it's strong characteristics for ambiguity and might retain rather more info than laborious segmentation methods [15]. Though the standard FCM formula works well on most noise-free pictures, it's terribly sensitive to noise and different imaging artifacts, since it doesn't think about any info concerning spacial context.

To compensate this downside of FCM, a pre-processing image smoothing step has been planned in [13], [16], and [17]. However, by victimization smoothing filters necessary image details are often lost particularly boundaries or edges. Moreover, there are no thanks to management the trade-off between smoothing and agglomeration. Thus, several researchers have incorporated local spacial info into the first FCM formula to improve the performance of image segmentation [9], [15], [18]. Tolias and Panas [9] developed a fuzzy rule-based scheme known as the ruled-based neighborhood improvement system to impose spacial constraints by post process the FCM agglomeration results. Noordam et al. [10] planned a geometrically radio-controlled FCM (GG-FCM) formula, a semi-supervised FCM technique, wherever a geometrical condition is employed determined by taking under consideration the native neighborhood of every picture element. Pham [19] changed the FCM objective operates by including spacial penalty on the membership functions. The penalty term results in associate reiterative formula that is extremely similar to the first FCM and permits the estimation of spatially swish membership functions. Ahmed et al. [13] planned FCM_S wherever the target function of the classical FCM is changed so as to compensate the intensity in homogeneity and permit the labeling of a picture element to be influenced by the labels in its immediate neighborhood. One disadvantage of FCM_S is that the neighborhood labeling is computed in every iteration step, one thing that's terribly long. Chen and Zhang [16] planned FCM_S1 and FCM_S2, two variants of FCM_S formula so as to cut back the computational time. These 2 algorithms introduced the extra mean and median-filtered image, severally, which can be computed earlier, to exchange the neighborhood term of FCM_S. Thus, the execution times of each FCM_S1 and FCM_S2 square measure significantly reduced. Afterward, Chen and Zhang [16] improved the FCM_S objective operate to a lot of doubtless reveal inherent nonEuclidean structures in information and a lot of lustiness to noise. They then replaced the geometrician distance by a kernelinduced distance and planned kernel versions of FCM with spatial constraints, known as KFCM_S1 and KFCM_S2. However, the most downside of FCM_S and its variants FCM_S1 and FCM_S2 and KFCM_S1 and KFCM_S2 is that their parameters heavily have an effect on the ultimate agglomeration results. Szilagyi et al. [17] planned the improved FCM (EnFCM) formula to accelerate the image segmentation process. The structure of the EnFCM is totally different from that of FCM_S and its variants. First, a linearly-weighted total image is made from each original image and every pixel's local neighborhood average grey level. Then agglomeration is performed on the premise of the grey level bar chart rather than pixels of the summed image. Since, the amount of grey levels in a picture is usually a lot of smaller than the amount of its

ISSN 2348-1196 (print)
International Journal of Computer Science and Information Technology Research ISSN 2348-120X (online)
Vol. 2, Issue 3, pp: (84-89), Month: July - September 2014, Available at: www.researchpublish.com

pixels, the process time of EnFCM formula is reduced, whereas the standard of the metameric image is comparable to that of FCM_S [17].Cai et al. [20] planned the quick generalized FCM algorithm (FGFCM) which includes the spacial information, the intensity of the native picture element neighborhood and the range of grey levels in a picture. This formula forms a nonlinearly-weighted total image from each original image and its native spacial and grey level neighborhood. The computational time of FGFCM is extremely little, since agglomeration is performed on the premise of the grey level bar chart. The quality of the metameric image is well increased [20]. In this paper, associate multi-kernel based mostly FCM (MKFCM) algorithm with spacial info has been planned victimization tow Gaussian kernels in situ of single kernel. Further, the membership values square measure changed by victimization their neighbors. The changed membership values square measure a lot of strong noise images. The effectiveness of the planned methodology is tested on four sample MRI brain pictures below totally different noise conditions and tried that the planned formula is a lot of robust as compared to FCM family algorithms. The organization paper is: In section I, a quick review of image segmentation given. A compendious review of FCM, KFCM, GKFCM and MKFCM is envisioned in section II. The planned MKFCM with spacial biasing is given in section III. Further, experimental results and discussions to support the formula are often seen in section IV. Conclusions are derived in section V.

## II. FUZZY C-MEAN ALGORITHMS (FCM)

### *A. commonplace FCM formula*

A fuzzy set-theoretic model provides a mechanism to represent and manipulate uncertainty inside a picture. The concept of fuzzy sets within which inexact information are often used to outline an occasion. Variety of fuzzy approaches for image segmentation square measure on the market. Fuzzy C-means is one in all the well-known agglomeration techniques Suppose a matrix of n information parts (image pixels), each of size s s( 1) □ is drawn as X x x x □ ( „....., ).1 2 n FCM establishes the agglomeration by iteratively minimizing the objective operate Objective function:

• The reiterative method starts:

1. Update the membership values Uij by victimization equivalent weight. (3).

2. Update the cluster centers Ci by victimization equivalent weight. (4).

3. Update the space D victimization equivalent weight. (2).

4. If C C new previous; (zero.001) then attend step1

5. Else stop

Assign every picture element to a selected cluster that the membership is maximal

### *B. FCM with spacial info*

To improve the lustiness of the FCM, FCM with special

Information is planned. FCM_S1 and FCM_S2 area unit Proposed by calculative the mean and median severally of the surround neighbors for a given component.

### *C. Kernel primarily based FCM*

Kernel version of the FCM rule and its objective function with the mapping Thus, the update equations for the required conditions for minimizing. We signifies that the required conditions for minimizing O U C m (,) area unit update Eqs. (8) and (9) only the kernel function K is chosen to be the Gaussian operate with 2 2

Completely different kernels can be chosen by exchange the geometrician distance for different functions. However, a Gaussian kernel is appropriate for clump during which it will really induce the required conditions. The higher than planned

KFCM rule is incredibly sensitive to the noise. To deal with this downside Chen and Zhang [16] have planned the KFCM_S1 and KFCM_S2 algorithms that area unit utilised the spacial neigh component information by introduce α parameter.

### *D. Gaussian Kernal FCM (GKFCM)*

It is mentioned that the parameter α is employed to manage the effect of the neighbors for adjusting the spacial bias correction term. In fact, the parameter α heavily affects the clustering results of KFCM_S1 and KFCM_S2. Intuitively, it would be higher if we will modify every spacial bias correction term individually for every cluster i. That is, the overall parameter α is healthier replaced with ή i

that is correlated to every cluster i. during this sense, Miin-Shen and Hsu-Shen [21] have thought-about the subsequent changed objective operate O U C m

### *E. Multiple-Kernal primarily based FCM (MKFCM)*

KFCM_S1, KFCM_S2 and GKFCM strategies area unit utilised only one kernel (Gaussian) operate however the multiple-kernel methods offer America an excellent tool to fuse data from different sources [22]. To clarify that, Long et. al [23] used the term ―multiple kernel‖ in a very wider sense than the one

i = 1,2,….C

i = 1,2,..C (11)

used in machine learning community. Within the machine learning community, ―multiple-kernel learning‖ refers to the learning exploitation Associate in Nursing ensemble of basis kernels (usually a linear ensemble), whose combination is optimized within the learning process.

### *F. MKFCM with spacial data*

Venu et al. [24] have prosed a generalized a completely unique multiple-kernel fuzzy c-means (FCM) (NMKFCM) methodology with spacial data for medical image segmentation. During this paper, NMKFCM is described as MKFCM_S1 and MKFCM_S2 for reader's clarity. The objective operate, cluster centers and membership functions for the planned methodology The planned methodology is powerful to noise for image segmentation application and therefore the same has been established from experimental results and discussion in section IV.

## III. EXPRIMENTAL RESULTS AND DISCUSSIONS

In order to verify the effectiveness of the planned algorithm, experiments were conducted on four brain MRIs [25] to check the performance of the planned rule with alternative existing strategies. The Open Access Series of Imaging Studies (OASIS) [25] may be a series of resonance imaging (MRI) dataset that's in public offered for study and analysis. This dataset consists of a cross-sectional assortment of 421 subjects aged eighteen to ninety six years. The performance of the proposed methodology is evaluated in terms of score, number of iterations and time. Fig. one illustrates the sample pictures selected for experimentation.

### *G. Score Calculation*

For examination segmentation results of various algorithms with a quantitative live, we have a tendency to use the comparison score Tables II-III summarize the performance of assorted strategies with completely different Gaussian and salt & pepper noise. The performance of the strategies is evaluated on the premise of score showing higher performance as compared to alternative existing methods (FCM, KFCM, GKFCM and MKFCM) in terms of score.

TABLE IV: analysis OF GKFCM_S2 INTERMS OF PSNR WITH completely different Gaussian NOISE level Image one Image a pair of Image three Image four Image five Image vi Image seven TABLE V: analysis OF MKFCM INTERMS OF

PSNR WITH completely different Gaussian NOISE level Image one Image a pair of Image three Image four Image five Image vi Image seven TABLE VI: analysis OF MKFCM_S1 INTERMS OF PSNR WITH completely different Gaussian NOISE Noise level Image one Image a pair of Image three Image four Image five Image vi Image seven TABLE VII: analysis OF MKFCM_S2 INTERMS OF PSNR WITH completely different Gaussian NOISE Noise level Image one Image a pair of Image three Image four Image five Image vi Image seven

## IV. CONCLUSIONS

In this paper, the performance of the varied fuzzy primarily based clustering algorithms area unit evaluated for medical image segmentation. The performance is tested on brain imaging that degraded by Gaussian noise demonstrates that the MKFCM_S1 performs additional strong to noise than alternative existing image segmentation rules from FCM family.

## REFERENCES

[1] X. Munoz, J. Freixenet, X. Cufi, and J. Marti, ―Strategies for image segmentation combining region and boundary data,‖ Pattern Recognition Letters, vol. 24, no. 1, pp. 375–392, 2003.

[2] D. Pham, C. Xu, and J. Prince, ―A survey of current strategies in medical image segmentation,‖ In Annual Review of medicine Engineering, vol. 2, pp. 315–337, 2000.

[3] Muhammad Ali Balafar, Abd.Rahman Ramli, M.Iqbal Saripan, Syamsiah Mashohor, ―Medical Image Segmentation exploitation Fuzzy CMean (Fcm), Bayesian methodology And User Interaction,‖ Proceedings of the 2008 International Conference on moving ridge Analysis and Pattern Recognition, pp. 68-73, Aug. 2008.

[4] László Szilágyi, Sándor M. Szilágyi, Balázs Benyó and Zoltán Benyó, ―Application of Hybrid c-Means clump Models in Inhomogeneity Compensation and adult male Brain Image Segmentation,‖ 5th International conference on Applied procedure Intelligence and IP ,pp.105-110, May. 2009.

[5] MacQueen,J.B. ―Some strategies for classification and Analysis of Multivariate Observations,"Proceedings of fifth Berkeley conference on Mathematical Statistics and chance. University of Calif. Press, pp. 281–297, 1967.

[6] Arthur D,Vassilvitskii S,"How Slow is that the k-means Method?," Proceedings of the 2006 conference on procedure pure mathematics , June. 2006.

[7] L. Zadeh, ―Fuzzy sets,‖ Inf. Control, vol. 8, pp. 338–353, 1965.

[8] J. Udupa and S. Samarasekera, ―Fuzzy connectedness and object definition: Theory, rule and applications in image segmentation,‖ Graphical Models and Image process, vol. 58, no. 3, pp. 246–261, 1996.

[9] Y. Tolias and S. Panas, ―Image segmentation by a fuzzy clump algorithm exploitation adaptive spatially affected membership functions, IEEE Transactions on Systems, Man, and information science, vol. 28, no. 3, pp. 359–369, Mar.1998.

[10] J. Noordam, W. van den Broek, and L. Buydens, ―Geometrically guided fuzzy C-means clump for variable image segmentation.

[11] M. Yang, Y. J. Hu, K. Lin, and C. C. Lin, Segmentation techniques for tissue differentiation in MRI of ophthalmology using fuzzy clustering algorithms,‖ Magnetic Resonance Imaging, vol. 20, no. 2, pp. 173–179, 2002.

[12] G. Karmakar and L. Dooley, ―A generic fuzzy rule based image segmentation algorithm,‖ Pattern Recognition Letters., vol. 23, no.10, pp.1215–1227, 2002.

[13] M. Ahmed, S. Yamany, N. Mohamed, A. Farag, and T. Moriarty, ―A modified fuzzy C-means algorithm for bias field estimation and segmentation of MRI data,‖ IEEE Transactions on Medical Imaging, vol. 21, no. 3, pp. 193–199, 2002.

[14] J. Bezdek, ―Pattern Recognition with Fuzzy Objective Function Algorithms, Kluwer Academic Publishers, New York: Plenum, 1981.

[15] D. Pham, An adaptive fuzzy C-means algorithm for image segmentation in the presence of intensity in homogeneities, Pattern Recognition Letters, vol. 20, pp. 57–68, 1999.

[16] S. Chen and D. Zhang, ―Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure, IEEE Transactions on Systems, Man, and Cybernetics, vol. 34, pp. 1907–1916, 2004.

[17] L. Szilagyi, Z. Benyo, S. Szilagyii, and H. Adam, ―MR brain image segmentation using an enhanced fuzzy C-means algorithm,‖ in Proceedings of the 25" Annual International Conference of the IEEE EMBS, pp. 17–21, 2003.

[18] M. Krinidis and I. Pitas, ―Color texture segmentation based-on the modal energy of deformable surfaces,‖ IEEE Transactions on Image Processing, vol. 18, no. 7, pp. 1613–1622, Jul. 2009.

[19] D. Pham, ―Fuzzy clustering with spatial constraints,‖ in Proceedings of International Conference on Image Processing, New York, 2002, vol. II, pp. 65–68.

[20] W. Cai, S. Chen, and D. Zhang, ―Fast and robust fuzzy c-means clustering algorithms incorporating local information for image segmentation,‖ Pattern Recognition, vol. 40, no. 3, pp. 825–838, Mar. 2007.

[21] Miin-Shen Yang, Hsu-Shen Tsai, ―A Gaussian kernel-based fuzzy cmeans algorithm with a spatial bias correction,‖ Pattern Recognition Letters, vol. 29, pp. 1713–1725, May 2008.

[22] G. Camps-Valls, L. Gomez-Chova, J. Munoz-Mari, J. L. RojoAlvarez, and M. Martinez-Ramon, ―Kernel-based framework for multitemporal and multisource remote sensing data classification and change detection,‖ IEEE Trans. Geosci. Remote Sens., vol. 46, no. 6, pp. 1822–1835, Jun. 2008.

[23] Long Chen, C. L. Philip Chen, and Mingzhu Lu, ―A Multiple-Kernel Fuzzy C-Means Algorithm for Image Segmentation,‖ IEEE Trans. Systems, Man, And Cybernetics—Part B: Cybernetics, vol. 41, No. 5, pp. 1263 – 1274, February 9,2011.

[24] NookalaVenu, Dr. B. Anuradha, A Novel Multiple-kernel based Fuzzy c-means Algorithm with Spatial Information for Medical Image Segmentation, International Journal of Image Processing (IJIP), Volume (7) : Issue (3) : 2013

[25] D. S.Marcus, T. H. Wang, J. Parker, J. G. Csernansky, J. C.Morris, and R. L. Buckner, Open access series of imaging studies (OASIS): Crosssectional MRI data in young, middle aged, non-demented, and demented older adults. J. Cogn. Neurosci., 19 (9) 1498–1507, 2007.

[26] Masulli, F., Schenone, A., 1999. A fuzzy clustering based segmentation system as support to diagnosis in medical imaging. Artif.Intell. Med. 16, 129–147.

[27] Zhang, D.Q., Chen, S.C., 2004. A novel kernelized fuzzy c-means algorithm with application in medical image segmentation. Artif.