Journal of Electrical and Electronic Engineering
2015; 3(1): 1-5
Published online January 19, 2015 (http://www.sciencepublishinggroup.com/j/jeee)
doi: 10.11648/j.jeee.20150301.11
ISSN: 2329-1613 (Print); ISSN: 2329-1605 (Online)

Improved fuzzy c-means algorithm for image segmentation

Xuegang Hu[1, 2], Lei Li[1]

[1]College of Computer Science and Technology, Chongqing University of Posts and Telecommunications, Chongqing, China
[2]Research Center of System Science, Chongqing University of Posts and Telecommunications, Chongqing, China

Email address:
marblelilei@163.com (Lei Li), huxg62461211@126.com (Xuegang Hu)

To cite this article:
Xuegang Hu, Lei Li. Improved Fuzzy C-Means Algorithm for Image Segmentation. *Journal of Electrical and Electronic Engineering.* Vol. 3, No. 1, 2015, pp. 1-5. doi: 10.11648/j.jeee.20150301.11

Abstract: In order to preserve more image details and enhance its robustness to noise for image segmentation, an improved fuzzy c-means algorithm (FCM) for image segmentation is presented by incorporating the local spatial information and gray level information in this paper. The modified membership function and clustering center function are more mathematically reasonable than those of the FLICM, so the iterative sequence can converge to a local minimum value of the improved objective function. The new fuzzy factor grants the algorithm a novel balance between robustness to noise and effectiveness of preserving the details. The revised algorithm flow has significantly accelerated the processing procedure. Through these improvements, the experiments on the artificial and real images show that the proposed algorithm is very effective.

Keywords: Clustering, Image Segmentation, Fuzzy C-Means, Local Minimum Value, Gray Level Information

1. Introduction

Image segmentation plays an important role in a variety of applications such as machine vision, image analysis and image understanding, so it is a hot topic in image processing in recent years [1]. Currently, the methods of image segmentation are broadly divided into four categories: threshold, clustering, edge detection and region extraction. Among the clustering-based methods, the fuzzy c-means algorithm (FCM) is one of the most popular methods of image segmentation, which was firstly proposed by Dunn [2] and improved later by many other scholars [3]. But the classic FCM algorithm and its improved ones are not suitable for images corrupted by noise, outliers and other imaging artifacts [4].

In recent years, incorporating local spatial information and gray level information to compensate the drawback above mentioned is becoming more and more popular. By introducing local spatial information in the objective function of the FCM, Ahmed *et al.* proposed an improved FCM algorithm (FCM_S) [5]. The main advantage of this method is good performance of noise-immunity, but the disadvantage is summarized as follows: First, the method lacks sufficient robustness to noise. Second, it can't present a non-Euclidean structure of the image data. Finally, it increases running time. Tolias *et al*. imposed space constraints on clustering results to modify the objective function of FCM and obtained some positive effects [6]. Pham introduced space term into the objective function of the FCM and significantly improved its noise-immunity capability [7]. In order to improve the anti-noise performance, robustness and reduce the processing time, Chen and Zhang proposed FCM_S1 and FCM_S2 based on FCM_S [8]. But the disadvantage is summarized as follows: it firstly lacks some robustness to noise and image speckle, it then needs some parameters chosen empirically, so it limits its application. Finally, the processing time depends on the size of the segmented image. To solve the above problems, Cai *et al.* put forward a generalized fast FCM (FGFCM) [9], the algorithm overcomes the above mentioned drawbacks of FCM_S to a certain extent and obtains better clustering performance, but the algorithm can't directly segment the color image, and some parameters need to be selected manually. In 2010, Krinidis and Chatzis proposed an improved FCM segmentation algorithm (FLICM) by integrating local spatial information and gray level information in the energy function [10]. It not only has better segmentation performance, but also doesn't need manual preselected parameters. However, Celik pointed out that the iterative sequence in the energy function doesn't converge to the minimum value because of the defects of FLICM, therefore, the FLICM segmentation results are not optimal [11]. Gong *et al.* presented a variant of FLICM algorithm (RFLICM) in 2012, whose spatial distance was replaced by local variable coefficient in the energy function [12]. Although the RFLICM algorithm exploits more local texture information, it ignores the relationship between the central pixel and its neighbor pixels. In 2013, Gong *et al.* further introduced weigh factors and nuclear distance parameters into its objective function and proposed the KWFLICM algorithm, this method have improved the segmentation results [13], but its processing time is significantly higher than that of the RFLICM.

To further improve the accuracy of image segmentation and reduce time consumption, using the new constraint factor instead of fuzzy constraint factor of the FLICM, we presented an improved fuzzy c-means algorithm for image segmentation. This algorithm enhances its robustness to noise and preserves more image details for image segmentation. Experimental results have showed that this method can quickly and accurately segment images such as synthetic and natural images, which has good anti-noise performance at the same time.

The rest of this paper is organized as follows. In Section 2, the classical fuzzy c-means clustering algorithm is briefly described. The proposed algorithm and our motivation are introduced in Section 3. Experimental results have showed in Section 4. Conclusions will be drawn finally.

2. Fuzzy C-Means Algorithm

The FCM algorithm for image segmentation is a clustering algorithm based on the most optimal function, its objective function is as follows

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ji}^m d^2(x_i, v_j), \tag{1}$$

where $X = \{x_1, x_2, \cdots, x_N\} \subseteq R^{N \times D}$ is the dataset in the images to be segmented. v_j denotes the center value of cluster j. $d^2(x_i, v_j)$ stands for a distance measure between dataset x_i and cluster center v_j. N is the number of gray levels of the image. c is the number of clusters with $2 \le c < N$. The parameter m determines the amount of fuzziness of the result classification between 1.5 and 2.5 [14], u_{ji} is the degree of membership of x_i in the j^{th} cluster satisfying

$$\sum_{j=1}^{c} u_{ji} = 1, \forall i \in \{1, 2, \cdots, N\}. \tag{2}$$

To calculate the possible extremum according to (2), an Euler-Lagrange function is used as follows

$$L(u_{ji}, v_j) = \sum_{i=1}^{N}\left(\sum_{j=1}^{c} u_{ji}^m \left\| x_i - v_j \right\|^2 + \lambda_i \left(1 - \sum_{j=1}^{c} u_{ji}\right)\right),$$

where λ_i is a parameter. And we can obtain the one order partial derivative of u_{ji} and v_j. According to (2), the values of membership and cluster centers can be calculated as follows

$$u_{ji}^* = 1 \Bigg/ \sum_{k=1}^{C}\left(\frac{\left\| x_i - v_j \right\|}{\left\| x_i - v_k \right\|}\right)^{2/(m-1)} \tag{3}$$

and

$$v_j^* = \sum_{i=1}^{N} u_{ji}^m x_i \Bigg/ \sum_{i=1}^{N} u_{ji}^m. \tag{4}$$

The classical FCM algorithm can acquire good segmentation effect, but it is very sensitive to noise. Therefore, many scholars are developing its anti-noise capability.

3. Fuzzy Local Information C- Means Cluster Algorithm

Because the classical FCM algorithm only considers the gray value of pixels and doesn't take into account the relationship between the center pixel and its neighbors. So it is not suitable for images corrupted by noise. The FLICM algorithm takes advantage of neighborhood information, which has some anti-noise performance. It not only reduces the accuracy of the FCM algorithm, but also exists some mathematically unreasonable functions. Motived by these considerations, we propose a modified method by reducing fuzzy constraint factor values of the FLICM to enhance the accuracy of image segmentation, so we can get a new balance between robustness to noise and effectiveness of preserving the details. The new algorithm's objective function is defined as follows

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{c}\left\{u_{ji}^m\left[\sum_{l=1}^{d}\left(x_{il} - v_{jl}\right)^2\right] + \sum_{\substack{p \in N_i \\ p \neq i}} \frac{1}{d_{ip}+1} u_{jp}^m e^{\frac{-\sum_{l=1}^{d}\left(x_{pl} - v_{jl}\right)^2}{\delta}}\right\}, \tag{5}$$

where d denotes the image dimension. d_{ip} is the spatial Euclidean distance between pixels i and j. x_{pl} is the neighborhood information of data item x_{il}. u_{jp} represents the fuzzy membership of the j^{th} pixel lying within a window around x_{il} with respect to cluster j, N_i is the dataset of neighbors falling into a window around x_{il}. δ is a distance variance that denotes the degree of aggregation around the cluster. Its definition shows as follows

$$\delta = \left(\frac{1}{N-1}\sum_{i=1}^{N}\left(d_i - \bar{d}\right)^2\right)^{\frac{1}{2}}.$$

Where $d_i = \left\| x_{il} - \bar{x} \right\|$, it is the distance from data item xil to the mean value of all pixels falling into the window. The mean distance of di is $\bar{d} = \sum_{i=1}^{N} d_i / N$.

To calculate the possible extremum according to (2), an Euler-Lagrange function is used as follows

$$L(u_{ji}, v_j) = \sum_{i=1}^{N}\sum_{j=1}^{C}\left(u_{ji}^m\left[\sum_{l=1}^{d}\left(x_{il} - v_{jl}\right)^2\right] + \right.$$

$$\sum_{p\in N_i, p\neq i}\frac{1}{d_{ip}+1}u_{jp}^{m}\exp\left(-\frac{1}{\delta}\sum_{l=1}^{d}\left(x_{pl}-v_{jl}\right)^2\right)+\lambda_i\left(1-\sum_{j=1}^{C}u_{ji}\right)\Bigg),$$

we can obtain the one order partial derivative of u_{ji} and v_j. Let $\frac{\partial L}{\partial u_{ji}}=0$ and, $\frac{\partial L}{\partial v_{jl}}=0$ we have

$$\frac{\partial L}{\partial u_{ji}}=mu_{ji}^{m-1}\left\|x_i-v_j\right\|^2-\lambda_i=0$$

and

$$\frac{\partial L}{\partial v_{jl}}=\sum_{i=1}^{N}\left\{u_{ji}^{m}\left(v_j-x_i\right)+\frac{1}{\delta}\sum_{\substack{p\in N_i\\ p\neq i}}\frac{1}{d_{ip}+1}u_{jp}^{m}\left(x_p-v_j\right)e^{\frac{-\left\|x_p-v_j\right\|^2}{\delta}}\right\}=0\,.$$

According to (2), the values of membership and cluster centers can be calculated as follows

$$u_{ji}^{*}=1\Bigg/\sum_{k=1}^{C}\frac{\left\|x_i-v_j\right\|^{\frac{2}{m-1}}}{\left\|x_i-v_k\right\|^{\frac{2}{m-1}}} \tag{6}$$

and

$$v_j^{*}=\frac{\sum_{i=1}^{N}\left(u_{ji}^{m}x_i-\frac{1}{\delta}\sum_{\substack{p\in N_i\\ p\neq i}}\frac{1}{d_{ip}+1}x_p u_{jp}^{m}e^{-\frac{\left\|x_p-v_l\right\|^2}{\delta}}\right)}{\sum_{i=1}^{N}\left(u_{ji}^{m}-\frac{1}{\delta}\sum_{\substack{p\in N_i\\ p\neq i}}\frac{1}{d_{ip}+1}u_{jp}^{m}e^{-\frac{\left\|x_p-v_l\right\|^2}{\delta}}\right)}\,. \tag{7}$$

Thus, the above algorithm is summarized as follows

Step 1: Fix the number m, ε, and c.

Step 2: Initialize the clustering center and calculate the initial membership matrix as described in Eq. (3).

Step 3: Set the loop counter b=0.

Step 4: Calculate the membership matrix as described in Eq. (6).

Step 5: Update the clustering center as described in Eq. (7).

Step 6: If max$\{V_{new}\text{-}V_{old}\}<\varepsilon$ then stop, otherwise, set b=b+1 and go to step 4.

4. Experimental Results and Analysis

In this section, we compare the accuracy, the efficiency and the robustness to noise of our algorithm with the FLICM algorithm. In the experiments, the code of the FLICM was provided by the authors.

Fig. 1 shows a synthetic image Synthetic's segmentation effect after mixed Speckle noise, the noise level is 15%. The size of Synthetic is 256*256 pixels. The gray level value of the left is 20, and the right is 120. We generally set the parameters to be c=2， ε=10^{-5}， m=1.7 .

Although the two algorithms worked well in the segmentation experiment, we still found that there are more "glitches" in Fig. 1 (c) than that in Fig. 1 (d). According to Fig. 1, we know that our method achieves better performance under Speckle noises than FLICM.

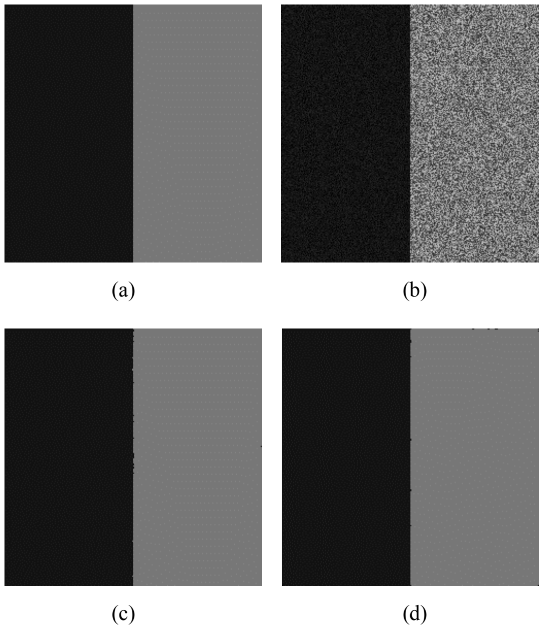


Fig. 1. *Segmentation results on Synthetic image. (a) Original image, (b) the same image corrupted by the Speckle noise (0.15), (c) FLICM result, (d) our result.*

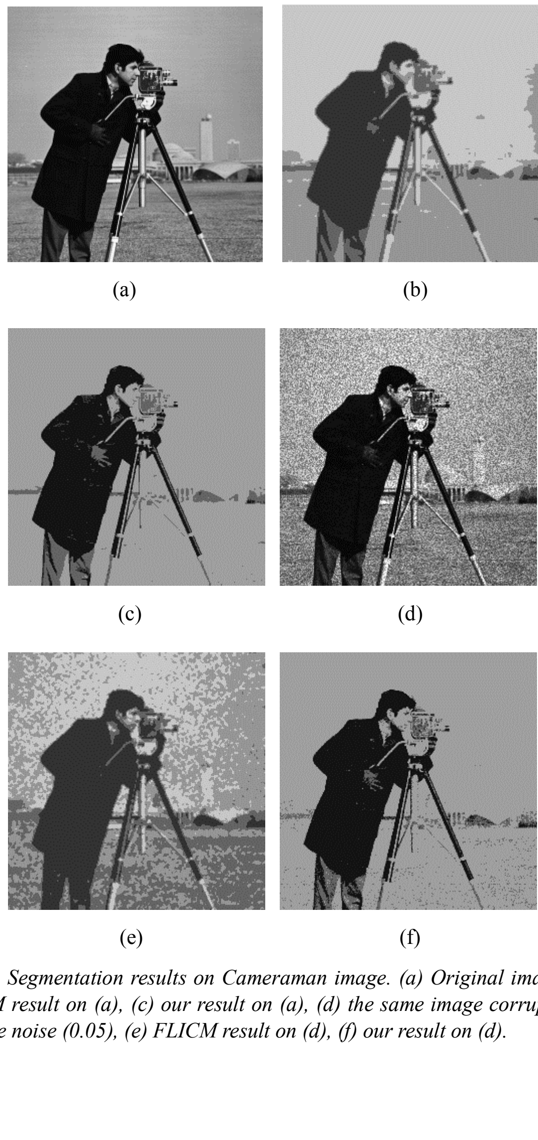


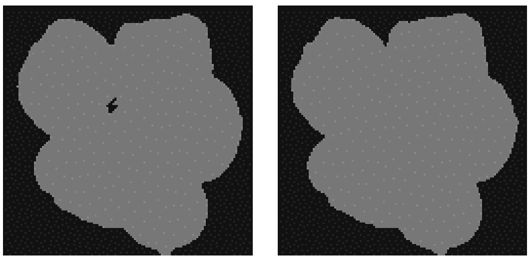
Fig. 2. *Segmentation results on Cameraman image. (a) Original image, (b) FLICM result on (a), (c) our result on (a), (d) the same image corrupted by Speckle noise (0.05), (e) FLICM result on (d), (f) our result on (d).*

Fig. 2 presents a comparison of segmentation results on a real image. In this experiment, the Cameraman image was divided into four categories-coats, trousers, skin and others. So the parameters was set to be $c=4$, $\varepsilon=10^{-5}$ and $m=1.7$.

In Fig. 2 (b), an obviously false segmentation area can be found on the right side, which should be a part of the sky information misclassified to another clustering, and there is no such a mistake in Fig. 2 (c). On the other hand, Fig. 2 (c) preserves more details than Fig. 2 (b) such as the hand and the edge of face. Due to the noise, the effect on Fig. 2 (e) is poor. But Fig. 2 (f) shows that the result from our method has much clearer edge and smoother regions while clearing almost added noises. This experiment suggests that our proposed algorithm can accurately segment images. Furthermore, it has good anti-noise performance at the same time.

Fig. 3 presents a comparison of segmentation results on a nature image. In this experiment, the Flower image was divided into two categories-flower and background. So the parameters was set to be $c=2$, $\varepsilon=10^{-5}$ and $m=1.7$.

(a)



(b) (c)

***Fig. 3**. Segmentation results on Flower image. (a) Original image, (b) FLICM result, (c) our result.*

In Fig. 3 (b), an obvious area is divided to the wrong area belonging to the flower area. But Fig. 3 (c) avoids this error generated. So our algorithm achieves better segmentation effect than the FLICM.

Furthermore, Fig. 4 shows some segmentation results on real images. The left column shows the original images, while the right column shows the segmentation results which obtained by the proposed algorithm.

Celik *et al.* found that the iterative sequence of the FLICM can't mathematically achieve to converge to a local minim because of the improper membership function and clustering center function [11], although it achieve good clustering result. In this paper, we have modified those functions by mathematical means. This is the main reason why the proposed algorithm achieves better segmentation effect than the FLICM.

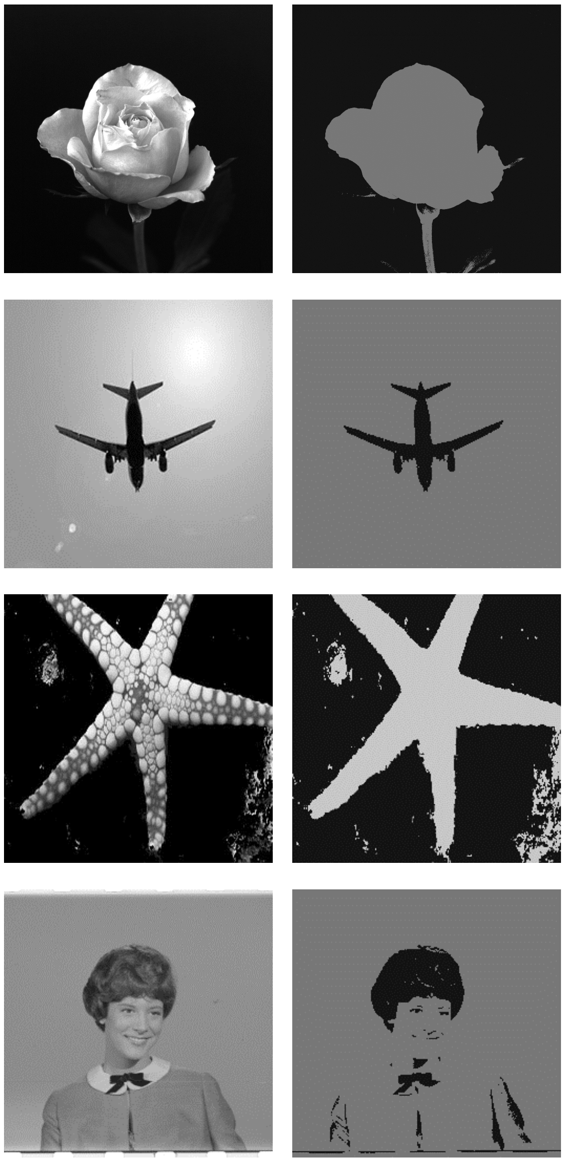


***Fig. 4**. Segmentation results on real images by the proposed algorithm*

Finally, Table 1 shows the comparison of the running time on different size images using the FLICM and our proposed algorithm. In this experiments, we generally set the parameters to be $c=3$, $\varepsilon=10^{-3}$, $m=2$ and $\max Iter=300$.

***Table 1.** Running Time (in seconds) of the Two Algorithms*

	200*200	300*300	600*600	1024*1024
FLICM	23.5	27.6	155.8	592.1
Our method	12.6	13.4	84.1	164.9

All experiments performed on an AMD Athlon(tm) 64 X2 Dual Core Processor 5400+ (2.8 GHz) workstation under Windows 7 Ultimate using MATLAB R2009a. As the result of running time is shown above, our algorithm is much faster than FLICM, especially, when the size of image is 1024*1024 pixels, the consumption time is only 27% of that of FLICM computed. This must owe to the novel algorithm flow. We initialize the membership matrix using Eq. (3) instead of initializing randomly it, so the value of initial membership matrix is more approximate to the final value. This modification has greatly decreased the iterative numbers.

5. Conclusions

In this paper, an improved algorithm based on FCM is proposed by modifying the fuzzy factor FLICM used. Through this way, we get a novel balance between robustness to noise and effectiveness of preserving the details. The results reported in this paper show that our method is effective to synthetic images, real images and nature images. The experiment results suggest that the proposed algorithm obviously improves the performance of image segmentation, which has good anti-noise performance at the same time.

So the major advantages of the proposed algorithm over the FLICM are summarized as follows:

- ✓ Its computational time is less;
- ✓ It preserves more image details;
- ✓ Its iterative functions are more mathematically reasonable.

Acknowledgements

The author would like to thank Dr. Krinidis for providing FLICM source codes for comparison, and the anonymous reviewers for their constructive comments.

References

[1] X. Muñoz, J. Freixenet, X. Cufı, *et al*, “Strategies for image segmentation combining region and boundary information,” Pattern recognition letters vol. 24, no. 1, pp. 375-392.

[2] J. Dunn, “A fuzzy relative of the ISO-DATA process and its use in detecting compact well separated clusters,” J. Cybern., vol. 3, no. 3, pp. 32-57, 1974.

[3] J. Bezdek, “Pattern recognition with fuzzy objective function algorithms,” New York: Plenum, 1981.

[4] Y. Liu, X. Wang, H. Yu, W. Zhang, “Brain tumor segmentation based on morphological multiscale modification and fuzzy c-means clustering,” Journal of Computer Applications, vol. 34, no. 9, pp. 2711-2715, 2014.

[5] M. Ahmed, S. Yamany, N. Mohamed, et al, “A modified fuzzy c-means algorithm for bias field estimation and segmentation of MRI data,” IEEE Trans. Med. Imag., vol. 21, no. 3, pp. 193-199, 2002.

[6] Y. Tolias and S. Panas, “Image segmentation by a fuzzy clustering algorithm using adaptive spatially constrained membership functions,” IEEE Trans. Syst., Man, Cybern., vol. 28, no. 3, pp. 359-369, Mar. 1998.

[7] D. Pham, “Fuzzy clustering with spatial constraints,” in Proc. Int. Conf. Image Processing. New Work, 2002, vol. Ⅱ, pp. 65-68.

[8] S. Chen, D. Zhang, “Robust image segmentation using FCM with spatial constraints based on new kernel-induced distance measure,” IEEE Trans. Syst., Man, Cybern., vol. 34, pp. 1907-1916, 2004.

[9] W. Cai, S. Chen, 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.

[10] S. Krinidis and V. Chatzis, “A robust fuzzy local information C-means clustering algorithm,” IEEE Trans. Image Process., vol. 19, no. 5, pp. 1328-1337, May 2010.

[11] T. Celik and H. Lee, “Comments on “A Robust Fuzzy Local Information C-Means Clustering Algorithm”,” IEEE Trans. Image Process, vol. 22, no. 3, pp. 1258-1261, 2013.

[12] M. Gong, Z. Zhou, J. Ma, “Change detection in synthetic aperture radar images based on image fusion and fuzzy clustering,” IEEE Trans. Image Process, vol. 21, no. 4, pp. 2141-2151, 2012.

[13] M. Gong, Y. Liang, J. Shi, *et al*, “Fuzzy c-means clustering with local information and kernel metric for image segmentation,” IEEE Trans. Image Process, vol. 22, no. 2, pp. 573-584, 2013.

[14] Pal, R. Nikhil and C. James, “On cluster validity for the fuzzy c-means model,” IEEE Trans. Fuzzy Syst. vol. 3, no. 3, pp. 370-379, 1995.