Australian Journal of Basic and Applied Sciences, 9(16) Special 2015, Pages: 268-274

ISSN:1991-8178

Australian Journal of Basic and Applied Sciences

Journal home page: www.ajbasweb.com

Suppressed Fuzzy C Means with Adaptive Non Local Spatial Information for segmentation of Noisy Images

[1]R. Meena Prakash, [2]R. Shantha Selva Kumari, [3]M. Vimala

[1]*Associate Professor, P.S.R Engineering college, Sivakasi, Tamil Nadu India.*
[2]*Professor, Mepco Schlenk Engineering college, Sivakasi, Tamil Nadu, India.*
[3]*PG Student, P.S.R Engineering college, Sivakasi, Tamil Nadu India.*

ARTICLE INFO

Article history:
Received 20 January 2015
Accepted 02 April 2015
Published 20 May 2015

Keywords:
Suppressed Fuzzy C Means,
Segmentation,
non local spatial information

ABSTRACT

In this paper, a new method for segmentation of images based on Fuzzy C Means Clustering is presented. The fuzzy c means is one of the clustering based methodologies. It has been extensively used for segmentation of images. Compared with the Hard C means clustering algorithm, it can retain more information in the image because of introducing fuzziness. The drawbacks of FCM are computational complexity and that the performance is degraded by noise. The computational complexity is overcome by Suppressed Fuzzy C Means which holds the biggest membership values and suppresses the other values. The impact of noise is reduced by incorporating the Non local spatial information derived from the pixels with a similar neighborhood configuration to the current pixel. In incorporating the non local spatial information, the selection of the filtering degree parameter h is a crucial problem and it depends on the noise level of the corrupted image. In the proposed method, the filtering degree parameter is made adaptive by employing the wavelet based robust median estimator. Experimental results obtained by employing the proposed method on synthetic images, real images from Berkeley dataset and simulated brain images from Brain web demonstrate the improved robustness and effectiveness of the method.

To Cite This Article: R. Meena Prakash, R. Shantha Selva Kumari, M. Vimala., Suppressed Fuzzy C Means with Adaptive Non Local Spatial Information for segmentation of Noisy Images. ***Aust. J. Basic & Appl. Sci.,*** *9(16): 268-274, 2015*

INTRODUCTION

Image segmentation is the process of partitioning the digital image into multiple segments. The main goal of segmentation is to change the representation of an image to something that is more meaningful and easier to understand. There are many segmentation methods in literature such as threshold based, region growing, Clustering, Model based and level set Approaches. Fuzzy C Means is one of the soft segmentation methods which assign membership value to each cluster at every pixel and then using them to assign the pixels to one or more cluster. (Bezdek, 1981). When compared with Hard C Means, Fuzzy C Means can retain more information because of introducing fuzziness for each pixel.

The drawbacks of FCM segmentation are that it has high computational complexity and that the method is sensitive to noise. To reduce the computational complexity, one of the methods is suppressed Fuzzy C Means (Fan *et al*. 2003) in which the non-winner memberships are suppressed while the winner values are increased. This method improves the convergence speed while preserving the classification accuracy. A method for selecting fixed suppressed rate by the distribution of the data is proposed (Fan *et al*., 2014). Possibility fuzzy – c means algorithm (Pal *et al*., 2005) is proposed in which memberships and possibilities are produced simultaneously along with cluster centers to overcome the noise sensitivity of FCM. Adaptive Fuzzy Clustering / Segmentation algorithm (Tolias *et al*., 2012) is proposed in which spatial constraints is imposed to the segmentation process. A wide range of methods for incorporating local spatial as well as gray information together in the FCM framework is introduced (Weiling *et al*., 2007).

(Buades *et al*., 2005) proposed Non-Local Means filter which defines the neighborhood J(i) of i by the condition: j ∈ J(i) if the gray level of a whole window around j is close to the gray level of the window around i. The spatial constraint is instead relaxed. Segmentation methods based on incorporating Non-Local Means spatial information are proposed.

Based on the above considerations, in this paper,

Corresponding Author: R. Meena Prakash, Associate Professor, P.S.R Engineering college, Sivakasi, Tamil Nadu India.

a new method for segmentation of noisy images is proposed. The non local spatial information for every pixel in the image is computed. In this, the estimation of the parameter h is done adaptively by using the robust median estimator (Grace *et al.* , 2000) based on the content of noise present in the image. Then, suppressed fuzzy - c means algorithm is applied to the non-local spatial information to get the segmented output. Since non local information is employed in the fuzzy c means segmentation, the proposed method outperforms the existing methods in the literature under noisy condition. Since suppressed fuzzy c means is employed, the method is computationally efficient. Since the parameter h is computed adaptively depending on the noise content of the image, the method is made simpler.

1. Suppressed Fuzzy c Means:

FCM clustering was developed by Bezdek and it is very widely used for image segmentation. Let X= $\{x_1, x_2 \ldots x_n\}$ denotes the set of data points to be partitioned into c clusters. The objective function of FCM to be minimized is defined as follows:

$$J_m = \sum_{k=1}^{c}\sum_{i=1}^{n} u_{ki}^{m} \|x_i - v_k\|^2 \quad (1)$$

$$where\ \textstyle\sum_{k=1}^{c} u_{ki} = 1,\quad u_{ki}\ \varepsilon\ [0,1]\ and$$
$$0 \le \textstyle\sum_{i=1}^{n} u_{ki} \le n$$

u_{ki} represents the membership function of i^{th} data point to k^{th} cluster, m>1 is the degree of fuzzification and v_k represents the k^{th} cluster center. By minimizing equation (1), the update equations for membership functions and cluster center are obtained as,

$$u_{ki} = \frac{1}{\sum_{l=1}^{c}\left(\frac{\|x_i - v_k\|^2}{\|x_i - v_l\|^2}\right)^{\frac{1}{m}}} \quad (2)$$

$$v_k = \frac{\sum_{i=1}^{n} u_{ki}^{m} X_i}{\sum_{i=1}^{n} u_{ki}^{m}} \quad (3)$$

Suppressed Fuzzy C Means Algorithm was introduced to speed up the FCM calculations. It reduces the execution time of FCM by improving the convergence speed, while preserving its good classification accuracy. If the degree of membership of x_i belonging to the pth cluster is the biggest of all the clusters, the value is noted as $u_{pi.}$ The memberships are modified as

$$u_{pi} = 1 - \propto \sum_{k \neq p} u_{ki} = 1 - \propto + \propto u_{pi} \quad (4)$$

The fuzzy memberships are then modified in such a way that all non-winner values are decreased via multiplying by a suppression rate α (0 ≤ α≤ 1) and the winner membership is increased accordingly. When α=0, FCM becomes HCM and when α=1, S-FCM becomes the FCM. Hence S-FCM can make a trade-off between HCM's fast convergence speed and FCM's good clustering performance.

The steps involved in SFCM are given below.

Step 1. Initialize the number of clusters c and cluster centers, $0 \le \propto \le 1$, m>1.

Step 2. Update the membership function matrix $U=\{u_{ki}\}$ by equation (2).

Step 3. Modify $U=\{u_{ki}\}$ by equation (4).

Step 4. Update cluster centers $V=\{v_i\}$ by equation (3).

The process gets repeated until the cluster centers stabilized.

2. Proposed Method:

Local Neighborhood filters introduce blurring effect in the image. The most similar pixels to a given pixel have no reason to be close to it. Hence it is fair to compute the spatial information by comparing a large window around each pixel and not the local neighborhood. For the i^{th} pixel, its spatial information is calculated by

$$v_i = \sum_{j \in W_i^r} w_{ij}\, x_j \quad (5)$$

Where W_i^r is r x r search window centered at the i^{th} pixel. The weight w_{ij} is the similarity between the neighborhood configuration of i^{th} pixel and j^{th} pixel.

$$w_{ij} = \frac{1}{Z_i} \sum_{j \in W_i^r} exp\left(-\|x(N_i) - x(N_j)\|_{2,\sigma}^{2} / h^2\right) \quad (6)$$

where $x(N_i)$ is a gray level vector of the pixels within a s x s square neighborhood N_i, centered at the i^{th} pixel and $x(N_j)$ is a gray level vector of the pixels within a s x s square neighborhood N_j, centered at the j^{th} pixel.

$(\|x(N_i) - x(N_j)\|_{2,\sigma}^{2}$ represents the Gaussian weighted Euclidean distance, where $\sigma > 0$ is the standard deviation of the Gaussian kernel. Hence the weight w_{ij} depends on the similarity between the neighborhood configurations of the i^{th} pixel and j^{th} pixel. The filtering degree parameter h in equation (7) can control the decay of the exponential function. Z_i is the normalizing constant and is defined as

$$Z_i = \sum_{j \in W_i^r} exp\left(-\|X(N_i) - X(N_j)\|_{2,\sigma}^{2} / h^2\right) \quad (7)$$

It is obvious from equations 5 and 6 that pixels with similar neighborhood configuration will be assigned with greater weights. The spatial information is derived from large regions of the image and hence this spatial information is called Non Local spatial Information. The selection of parameter h plays a major role in the computation of the non-local spatial information. If the value of h is large, the non local spatial information will lose the detail information in the image. If the value of h is small, then it cannot remove the effect of noise to the accepted value. The value of h strongly depends on the noise content present in the image.

The noise variance is estimated from sub band

HH1 of the wavelet decomposition of the image by the robust median estimator given by

$$h = \alpha\hat{\sigma};\ \hat{\sigma} = \frac{Median(|Y_{i,j}|)}{0.6745} \qquad Y_{i,j} \in \{HH_1\} \tag{8}$$

Where α is the multiplication factor and it is set as 0.87. It is reasonable to select α in the interval [0.75 1].

$\hat{\sigma}$ is the estimated noise standard deviation calculated from the image by taking wavelet decomposition.

The proposed method Suppressed Fuzzy C Means with Adaptive Non Local Spatial Information is explained in the following steps.

Step 1. Initialize the number of clusters c and cluster centers.

Step 2. Set the threshold (absolute difference between cluster centers calculated at successive iterations) as 0.00001.

Step 3. Compute the Non-Local Spatial information for every pixel. (window sizes r=21 and s=7). The parameter h is calculated as given in equation (8).

Step 4. Update the membership function matrix $U=\{u_{ki}\}$ by equation (2).

Step 5. Modify $U=\{u_{ki}\}$ by equation (4). Set α=0.5.

Step 6. Update cluster centers V= $\{v_i\}$ by equation (3).

The process gets repeated until the cluster centers stabilized on reaching the threshold.

The method is compared with Fuzzy Means and Suppressed Fuzzy C Means with Local Information. The local information for Suppressed Fuzzy – C Means is computed by filtering the noisy image with 3x3 mean filters.

4. Experimental Results:

In this section, the performance of the method on synthetic images, real images from Berkeley dataset and simulated MR brain images from Brain web dataset are presented. The system configuration used is Intel Core 2 Duo CPU @2.53GHz with 1.98GB of RAM. The algorithm is carried out using MATLAB. The Segmentation Accuracy (SA) employed to compare the effects obtained.

$$SA = \frac{No.of\ Correctly\ classified\ pixels}{Total\ number\ of\ pixels} \tag{9}$$

The Segmentation Accuracy obtained with the proposed method is compared with that of Fuzzy C Means, Suppressed Fuzzy C Means with local spatial information and with the method (Fan *et al*., 2014).

A. Synthetic Images:

Two synthetic images are taken at a resolution of 256 x 256. Both the images include four clusters with means 0, 85, 170 and 255 and shown in Fig. 1 (a) and Fig. 2 (a). Gaussian noise of zero mean and 0.024 normalized variance is added to these synthetic images, and the noisy images shown in Fig. 1 (b) and Fig. 2 (b). The Segmentation Results of FCM, S-FCM and the proposed method are shown in Fig. 1 (c)-(e) and Fig. 2 (c)-(e).

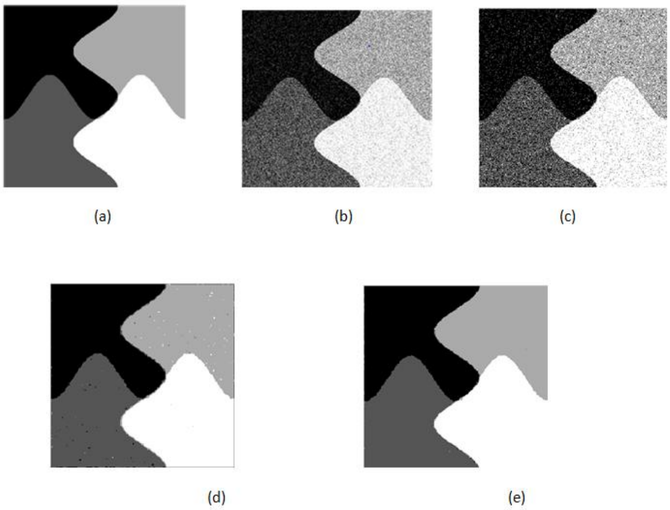

Fig. 1: Segmentation results on the synthetic Image 1 (a) Original Image (b) Image added with Gaussian noise (mean 0 and variance 0.024) (c) FCM (SA=0. 7894) (d) S-FCM with local spatial information (SA=0.9801) (e) Proposed Method (SA=0.9920).

B. Real Images from Berkeley dataset:

Three Berkeley Images #238001, #167062 and #42049 as taken in [13] and their respective ground truths are shown in Fig. 3 (a) - (f). Gaussian Noise is added to these images as #238001 image (mean Zero and 0.005 variance), #167062 (mean zero and 0.01 variance) and #42029 (mean zero and 0.03 variance). The segmentation results of FCM, S-FCM with local information and the proposed method are shown in Fig. 4 (a)-(c) ,5 (a)-(c) and 6 (a)-(c).

Australian Journal of Basic and Applied Sciences, 9(16) Special 2015, Pages: 268-274

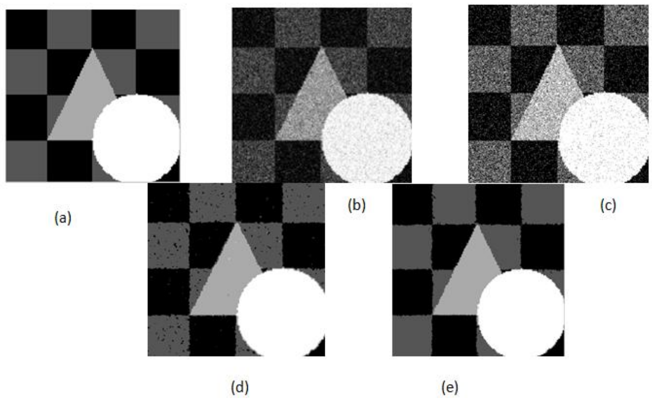

Fig. 2: Segmentation results on the synthetic Image 2 (a) Original Image (b) Image added with Gaussian noise (mean 0 and variance 0.024) (c) FCM (SA=0. 0.7742); (d) S-FCM with local spatial information (SA=0.9768); (e) Proposed Method (SA=0.0.9865).

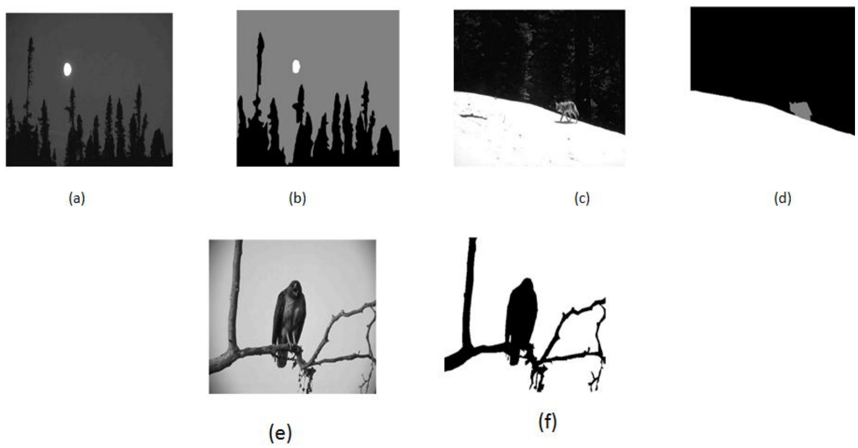

Fig. 3: Berkeley Images (a) #238001 image (b) ground truth of #238001 (c) #167062 image (d) ground truth of #167062 (e) #42049 image(f) (b) ground truth of #42049.

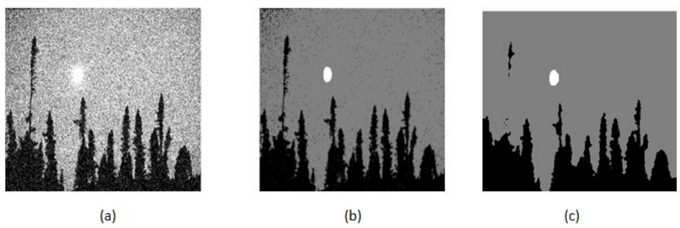

Fig. 4: Segmentation results on the Berkeley dataset #238001 image (a) FCM (SA=0.7209) (b) S-FCM with local information (SA= 0.9573) (c) Proposed Method (SA= 0.9807).

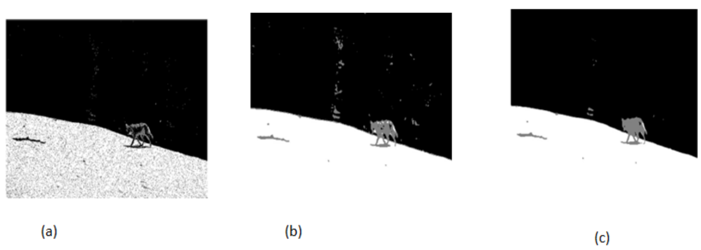

Fig. 5: Segmentation results on the Berkeley dataset #167062 image (a) FCM (SA=0.8523) (b) S-FCM with local information (SA=0.9701) (c) Proposed Method (SA=0.9913).

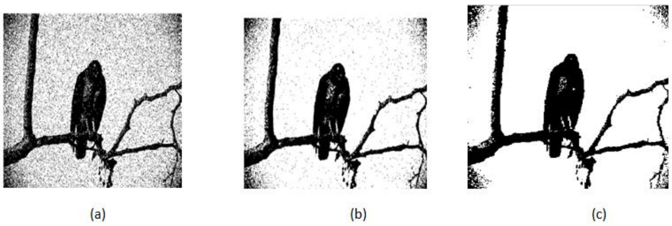

Fig. 6: Segmentation results on the Berkeley dataset #42049 image (a) FCM (SA=0.8414) (b) S-FCM with local information (SA=0.9412) (c) Proposed Method (SA=0.9633).

Table 1: Comparison of SA of FCM, S-FCM with local information, Method (Fan *et al*., 2014) and Proposed Method for Synthetic Images.

Images	FCM	S-FCM with local information	Method (Fan *et al*., 2014)	Proposed Method
Synthetic Image 1	0.7894	0.9801	0.9923	0.9920
Synthetic Image 2	0.7742	0.9768	-	0.9865

Table 2: Comparison of FCM, S-FCM with local information, Method (Fan *et al*., 2014) and Proposed Method for Images from Berkely dataset.

Images	FCM	S-FCM with local information	Method (Fan *et al*., 2014)	Proposed Method
#238001	0.7209	0.9573	0.9609	0.9807
#167062	0.8523	0.9701	0.9911	0.9913
#42049	0.8414	0.9412	0.9614	0.9633

Table 3: Comparison of Number of Iterations for FCM and S-FCM with local information.

Image	FCM	S-FCM with local information
Synthetic Image 1	57	11
Synthetic Image 2	102	12
#238001	43	17
#167062	51	23
#42049	20	13

It is inferred from Table 1, 2 and 3 that the proposed method provides superior results compared to FCM and SFCM with local information for both synthetic images and real images by a quantitative value of around 26% (FCM) and 12% (SFCM with local information) respectively. Also, since Suppressed Fuzzy C Means is employed, the computational complexity is reduced by more than 35%.

C. Simulated Images from Brain web:

The proposed method is also tested on T1-weighted MR brain images from the Brain web database. The method is validated on simulated images with 40% inhomogeneity and 9% noise 181 x 217 x 181 dimension 1 x 1 x 1 mm^3 spacing.

The ground truth for the Brain Web dataset is the phantom atlas used to generate the simulated scans. The Dice Similarity Index (DSI) is used to evaluate the performance. The Dice Similarity Index DSI S (j) is defined
as:

$$DSI = S(j) = \frac{2N_{P\cap g}(j)}{N_p(j) + N_g(j)} \tag{9}$$

Where $N_{P\cap g}(j)$ is the number of pixels classified as class j by both the proposed method and the ground truth. $N_p(j)$ and $N_g(j)$ represent the number of pixels classified as class j by the proposed method and by the ground truth, respectively.

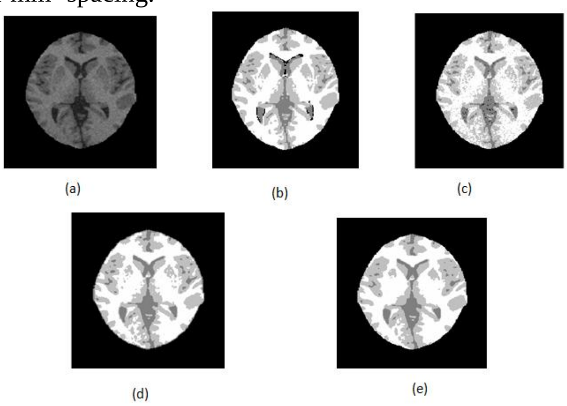

Fig. 7: Segmentation results on the MR Brain Image Slice #75 (a) original Image (b) Ground truth Image (c)

FCM (d) S-FCM with local information (e) Proposed Method (h=10).

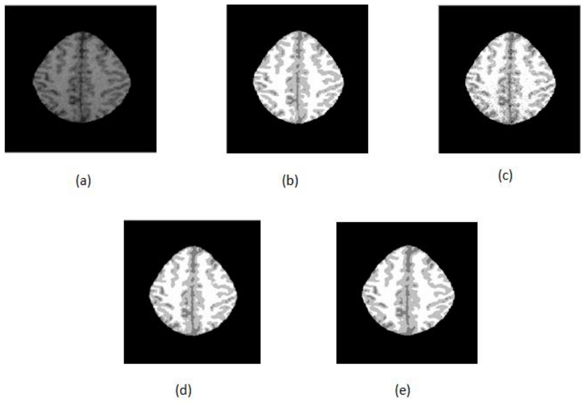

Fig. 8: Segmentation results on the MR Brain Image Slice #120 (a) original Image (b) Ground truth Image (c) FCM (d) S-FCM with local information (e) Proposed method (h=10).

Two simulated images (#75 and #120) from Brainweb dataset are taken at a resolution of 256 x 256. The brain image is segmented into three classes Cerebro-spinal Fluid with pixel value 128, Gray matter with pixel value 192 and White matter with pixel value 254. The original images are shown Fig. 7 (a) and Fig. 8 (a). The ground truths of the images are shown in Fig. 7 (b) and Fig. 8 (b). The segmentation results of FCM, S-FCM with local information and proposed method are shown in Fig. 7 (c) - (e) and Fig. 8 (c) - (e).

Table 4: Comparison of Dice Similarity Index and no. of iterations for GM and WM of FCM and S-FCM with local information for simulated brain images from Berkeley dataset.

Class	FCM		S-FCM with local information		Proposed Method (h=10)
	DSI	No. of iterations	DSI	No. of iterations	DSI
GM (#75)	0.8073	53	0.8387	23	0.8617
WM (#75)	0.8662	53	0.9004	23	0.9120
GM (#120)	0.7905	86	0.8530	33	0.8769
WM (#120)	0.8814	86	0.9072	33	0.9150

It is inferred that the proposed method is superior to FCM and SFCM with local information by 6% and 3% respectively

5. Conclusion:

This Paper proposes a new method for segmentation of noisy images. Since Suppressed Fuzzy C - Means is employed; the computational complexity of FCM is greatly reduced. The Non Local spatial Information is considered for each pixel and hence the segmentation accuracy is improved compared to the methods using local spatial information. Also, the parameter h in the non-local information computation is made adaptive by estimating the noise variance of the image which makes the method simpler compared to the existing methods. Experimental results obtained by employing the proposed method on synthetic images, real images from Berkeley dataset and simulated brain images demonstrate the improved robustness and effectiveness of the method.

REFERENCES

Bezdek, J.C., 1981. Pattern recognition with fuzzy objective function algorithms. New York: *Plenum*.

Buades, A., B. Coll, J.M. Morel, 2008. “Nonlocal image and movie denoising”, International *Journal of Computer Vision*, 76: 123-139.

Fan, J.L., W.Z. Zhen, W.X. Xie, 2003. “Suppressed fuzzy c-means clustering algorithm”, *Pattern Recognition Letter*, 24: 1607-1612.

Buades, A., B. Coll, J.M. Morel, 2005. “A non-local algorithm for image denoising”, In IEEE international conference on computer vision and pattern recognition.

Feng Zhao, Licheng Jiao, Hanqiang Liu, 2011. “Fuzzy c-means clustering with non local spatial information for noisy image segmentation” *Frontiers of Computer Science,* 5(1): 45-56.

Feng Zhao, Jiulun Fan, Hanqiang Liu, 2014. “Optimal-selection-based suppressed fuzzy c-means clustering algorithm with self-tuning non local spatial information for image segmentation” *Expert Systems with Applications,* 41: 4083-4093.

Feng Zhao, Licheng Jiao, Hanqiang Liu, 2013. “Kernel generalized fuzzy c-means clustering with spatial informationfor image segmentation”, *Digital Signal Processing,* 23: 184-199.

Liu, H.Q., L.C. Jiao, F. Zhao, 2010. “Non-local spatial spectral clustering for image segmentation” *Neurocomputing*, 74: 461-471.

Hui Zhang, Qing Ming Jonathan Wu, Yuhui Zheng, Thanh Minh Nguyen, Dingcheng Wang, 2014. “Effective fuzzy clustering algorithm with

Bayesian model and mean template for image segmentation” *IET Image Processing*, 8(10): 571-581.

Jiulun Fan, Jing Li, 2014. “A Fixed Suppressed Rate Selection Method for Suppressed Fuzzy C-Means Clustering Algorithm” *Applied Mathematics*, 5: 1275-1283.

Keh-Shih Chuang, Hong-Long Tzeng, Sharon Chen, Jay Wu, Tzong-Jer Chen, 2006. “Fuzzy c-means clustering with spatial information for image segmentation”, *Computerized Medical Imaging and Graphics,* 30: 9-15.

Pal, N., K. Pal, J. Bezdek, 2005. “A Possibilistic fuzzy c-means clustering algorithm”, *IEEE Transactions on Fuzzy Systems*, 13(4): 517-530.

Shreyamsha Kumar, B.K., 2013. “Image denoising based on Gaussian/bilateral filter and its method noise thresholding”, *Signal, Image and Video Processing*, 7(6): 1159-1172.

Weiling Cai, Songcan Chen, Daoqiang Zhang, 2007. “Fast and robust fuzzy *c*-means clustering algorithms incorporating local information for image segmentation” *Pattern Recognition,* 40: 825-838.

Yanyan He, M. Yousuff Hussaini, Jianwei Ma, Behrang Shafei, Gabriele Steidl, 2012. “A new fuzzy c-means method with total variation regularization for segmentation of images with noisy and incomplete data”, *Pattern Recognition,* 45: 3463-3471.

Yannis A. Tolias and Stavros M. Panas, 1998. “Image Segmentation by a Fuzzy Clustering Algorithm Using Adaptive Spatially Constrained Membership Functions”, *IEEE Transactions on Systems, Man, And Cybernetics-Part A: Systems And Humans*, 28(3): 359-369.

Zexuan Ji, Yong Xiab, Qiang Chena, Quansen Suna, Deshen Xia, David Dagan Feng, 2012. “Fuzzy c-means clustering with weighted image patch for image segmentation”, *Applied Soft Computing*, 12: 1659-1667.

Zhao Zaixin, Cheng Lizhi, Cheng Guangquan, 2014. “Neighbourhood weighted fuzzy c-means clustering algorithm for image segmentation”, *IET Image Processing,* 8(3): 150-161.

Brain Web-http://www.bic.mni.mcgill.ca/brainweb/. Simulated Brain Database at the McConnell Brain Imaging Centre of the Montreal Neurological Institute (MNI), McGill University images.

http://www.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/.

The Berkeley Segmentation Dataset.