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Evaluation of Integrated Hyperbolic Tangent and Gaussian Kernels Functions for Medical Image Segmentation

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Abstract
In this paper, a new segmentation algorithm by integrating the hyperbolic tangent and Gaussian kernels for fuzzy c-means (HGFCM) algorithm with spatial information is proposed for medical image segmentation. The evaluation of Fuzzy c-means (FCM) algorithm in terms of Vpc, Vpe and Silhouette value for medical image segmentation. The proposed method uses the combined kernels of hyperbolic tangent function and Gaussian kernel with the spatial information of neighboring pixels for clustering of images. The performance of the proposed algorithm is tested on OASIS-MRI image dataset. The performance is tested in terms of Vpc, Vpe and Silhouette Value on OASIS-MRI dataset. The results after investigation, the proposed method shows a significant improvement as compared to other existing methods in terms of PSNR under different Gaussian noises on OASIS-MRI dataset.

Keywords: FCM, hyperbolic tangent function, Image Segmentation, Gaussian Kernal, fuzzy, multiple-kernal.

1. Introduction
Image segmentation an active research area in medical image analysis. Image segmentation is ia also known as the division of image into sub-regions which are standardized with respect to some features such as tone, gray values, color, texture, etc. The image segmentation can be classified into four types: clustering, thresholding, edge detection and extraction of region. The clustering based method is considered in this paper for image segmentation.
In medical imaging, the magnetic resonance imaging (MRI) is the well known and popular technique. It is mainly because of its good resolution and contrast, which plays an important role in investigative imaging modalities. However, MRI suffers with three important problems: noises (additive and multiplicative noises), artefacts, and intensity in uniformity [1].
In literature, several techniques are available for medical image segmentation. The previously available literature on segmentation methods are: thresholding techniques [2], clustering techniques [3], classifiers based techniques [4], region growing techniques [5], Artificial Neural Networks (ANNs) based techniques [6], Markov Random Field (MRF) [7] models atlas-guided techniques etc. Amongst the above discussed methods, the clustering based techniques show an importance in medical imaging research.
Clustering is a procedure for classifying patterns or objects in such a manner that samples of the same cluster are more comparable to one another than samples belonging to other clusters. There are two main clustering approaches: the hard clustering technique and the fuzzy clustering technique. MacQueen [8] has proposed the k-means clustering algorithm. The k-means is one of the hard clustering technique. The usual hard clustering techniques classify every point of the records set just to one cluster. As a effect, the results are often very crusty, i.e., in image clustering every pixel of the image goes to one cluster. However, in many real conditions, issues such as restricted spatial resolution, reduced contrast, partly cover intensities, noise and intensity in homogeneities decrease the efficiency of hard (crusty) clustering techniques. Fuzzy set theory [9] has bring in the idea of incomplete membership, explained by a membership function. Fuzzy clustering, as a soft segmentation technique, has been extensively analyzed and effectively applied in image segmentation and clustering [10]–[19]. Among the fuzzy clustering techniques, fuzzy c-means (FCM) algorithm [10] is the generally well-liked technique which is used in image segmentation due to its robust features for uncertainty and can keep much more information as compared to hard segmentation techniques [11]. While the standard FCM algorithm works fit on most noise-free images, it is very aware to noise and other imaging artifacts, because it does not consider any data about spatial background.
Tolias and Panas [12] have proposed a fuzzy rule-based technique also known the ruled-based neighborhood improvement system to impress spatial constraints by post processing the FCM clustering results. Noordam et al. [13] have proposed a geometrically guided FCM (GG-FCM) algorithm which is a semi-supervised FCM technique. Here, a geometrical condition is used the local neighborhood of every pixel. Pham [14] has customized the FCM objective function by counting spatial punishment on the membership functions. The punishment term leads to an iterative algorithm, which is extremely comparable to the original FCM and allows the evaluation of spatially flat membership functions. Ahmed et al. [15] have proposed the FCM_S where the objective function of the standard FCM is modified in order to recompense the intensity in uniformity and permit the labeling of a pixel to be effected by the labels in its neighborhood. The disadvantage of FCM_S is that the neighborhood labeling is computed in every iteration step which is very time-consuming.
Chen and Zhang [16] have proposed FCM_S1 and FCM_S2 which are the two variants of FCM_S algorithm in order to decrease the computational complexity. These two techniques introduced the additional mean and median-filtered image,

respectively, which can be calculated in advance, to swap the neighborhood term of FCM_S. Thus, the implementation times of both FCM_S1 and FCM_S2 are significantly decreased. Further, they have enhanced the FCM_S objective function to more likely disclose intrinsic non-Euclidean structures in data and more robustness to noise. They then replaced the Euclidean distance by a kernel-induced distance and proposed kernel versions of FCM with spatial constraints also known as KFCM_S1 and KFCM_S2 [16]. However, the major disadvantage of FCM_S and its variants is that their parameters greatly change the finishing clustering results.

Szilagyi et al. [17] have proposed the enhanced FCM (EnFCM) algorithm to go faster the image segmentation procedure. The structure of the EnFCM is changed from that of FCM_S and its variants. First, a linearly-weighted sum image is created from both original image and every pixel's local neighborhood average gray scales. Then clustering is conducted on the basis of the gray scale histogram as an alternative of pixels of the summed image. Because the number of gray scales in an image is usually much less important than the number of its pixels, the computational complexity of EnFCM algorithm is decreased, as the quality of the segmented image is equivalent to that of FCM_S [17]. Cai et al. [20] have proposed the fast generalized FCM algorithm (FGFCM) which uses the spatial information also known as the intensity of the local pixel neighborhood and the number of gray scales in an image. This technique forms a nonlinearly-weighted sum image from both original image and its local spatial and gray scale neighborhood. The computational complexity of FGFCM is very little, because clustering is carried out on the basis of the gray scale histogram. The excellence of the segmented image is fine enhanced [20]. Yang and Tsai [21] have proposed the Gaussian kernel based FCM (GKFCM) for medical image segmentation. The proposed GKFCM algorithm becomes a generalized type of FCM, KFCM_S1 and KFCM_S2 algorithms and presents with more efficiency and robustness. Chen et al. [22] have proposed the multiple-kernel fuzzy C-means (FCM) (MKFCM) for image-segmentation problems. They have used the linear combination of multiple kernels as composite kernel.

Kannan et al. [23] have proposed the hyper tangent FCM (HTFCM)based image segmentation for breast images. They have used the hyper tangent function as objective function in place of original Euclidean distance on feature space. Venu et al. [24] have proposed the segmentation algorithm (HGFCM) which integrates the hyperbolic tangent and Gaussian kernel functions for MRI image segmentation. Faruquzzaman et al. [25] have proposed the Robust Object Segmentation using Split-and-Merge (ROSSM). Sara et al. [26] have proposed and automatic fuzzy-neural based segmentation of microscopic cell images.

The main contributions of this paper are given as follows. (a) A hyperbolic tangent fuzzy C-means with spatial information (HTFCM_S1 and HTFCM_S2) algorithm which integrates the concepts of HTFCM and GKFCM. (b) The performance of the proposed method is tested on OASIS-MRI image data under noise conditions. (c) The segmentation results show a significant improvement as compared to other existing methods.

The organization of the paper is given as follows. Sections 1, presents the literature and related work of proposed clustering algorithms. The various methods which are available for cluster based segmentations are given in section 2, Section 3, presents the evaluation measures and dataset used in this paper. The experimental results and discussions are given in section 4. Conclusions are derived in section 5.

2. Methods

A. *Fuzzy C-means Algorithm*

A fuzzy set-theoretic representation illustrates a method to represent and control uncertainty within the image. The idea of fuzzy sets in which imprecise information can be used to describe an occurrence. A number of fuzzy techniques for image segmentation are accessible. The Fuzzy C-means is one of the famous clustering techniques

Fuzzy c-means clustering technique is a simplification of the hard c-means algorithm yields enormously superior results in image region clustering and object categorization. As in hard k-means algorithm, Fuzzy c-means algorithm is based on the minimization of a standard function.

Let a matrix of n data elements (image pixels), each of size $s(s=1)$ is represented as $X=(x_1,x_2,.....,x_n)$. FCM generates the clustering by iteratively minimizing the objective function given in Eq. (1).

Objective function: $$O_m(U,C)=\sum_{i=1}^{c}\sum_{j=1}^{n}U_{ij}^{m}D^2(x_j,C_i) \qquad (1)$$

Constraint: $$\sum_{i=1}^{c}U_{ij}=1; \quad \forall j \qquad (2)$$

Where, U_{ij} is membership of the j^{th} data in the i^{th} cluster C_i, m is fuzziness of the system (m=2) and D is the distance between the cluster center and pixel.

FCM algorithm

Fig. 1 illustrates the flow chart of FCM algorithm and the algorithm for the same is given bellow.

Input: Raw image; Output: Segmented image;

- Randomly initialize the cluster centers C_i ($c=3$ clusters).
- The distance D between the cluster center and pixel is calculated by using Eq. (3).

$$D^2(x_j,C_i)=\left\|x_j-C_i\right\|^2 \qquad (3)$$

- The membership values are calculated by using Eq. (4).

$$U_{ij}=\frac{D(x_j,C_i)^{-1/(m-1)}}{\sum_{k=1}^{c}D(x_j,C_k)^{-1/(m-1)}} \qquad (4)$$

- Update the cluster centers.

$$C_i=\frac{\sum_{j=1}^{n}U_{ij}^{m}x_j}{\sum_{j=1}^{n}U_{ij}^{m}} \qquad (5)$$

- The iterative process starts:

1. Update the membership values U_{ij} by using Eq. (4).
2. Update the cluster centers C_i by using Eq. (5).
3. Update the distance D using Eq. (3).
4. If $\left|C_{new}-C_{old}\right|>\varepsilon;\quad (\varepsilon=0.001)$ then go to step1
5. Else stop

Assign each pixel to a specific cluster for which the membership value is maximal

B. *Kernel Based FCM*

Kernel version of the FCM algorithm and its objective function are given bellow:

Objective function: $O_m(U,C)=\sum_{i=1}^{c}\sum_{j=1}^{n}U_{ij}^{m}(1-K(x_j,C_i))$ (6)

Thus, the revise equations for the essential conditions for minimizing $O_m(U,C)$ are given bellow:

$$C_i=\frac{\sum_{j=1}^{n}U_{ij}^{m}K(x_j,C_i)x_j}{\sum_{j=1}^{n}U_{ij}^{m}K(x_j,C_i)};\ i=1,2,....C \tag{7}$$

$$U_{ij}=\frac{\left(1-K(x_j,C_i)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(1-K(x_j,C_i)\right)^{-1/(m-1)}};\quad \begin{matrix} i=1,2,....C \\ j=1,2,..,n \end{matrix} \tag{8}$$

We identify the essential conditions for minimizing $O_m(U,C)$ are revise Eqs. (7) and (8) only when the kernel function K is selected to be the Gaussian function with $K(x_j,C_i)=\exp(-\|x_j-C_i\|^2/\sigma^2)$. Different kernels can be selected by replacing the Euclidean distance for different conditions. However, a Gaussian kernel is appropriate for clustering in which it can essentially make the essential conditions. The above proposed KFCM algorithm is very sensitive to the noise conditions. To solve this difficulty Chen and Zhang [16] have introduced the KFCM_S1 and KFCM_S2 techniques which are utilized the spatial data by bring α parameter.

C. *Gaussian Kernal FCM (GKFCM)*

Yang and Tsai [21] have proposed the Gaussian kernel based FCM (GKFCM) for medical image segmentation. The proposed GKFCM algorithm becomes a generalized type of FCM, KFCM_S1 and KFCM_S2 algorithms and presents with more efficiency and robustness. It is mentioned that the parameter α is used to manage the effect of the neighbors for adjusting the spatial bias alteration term. In fact, the parameter α greatly affects the clustering results of KFCM_S1 and KFCM_S2 techniques. Intuitively, it would be appropriate if we can correct each spatial bias alteration term independently for every cluster i. That is, the in general parameter α is better replaced with $\acute{\eta}_i$ that is correlated to each cluster i. In this sense, Yang and Tsai [21] have considered the modified objective function $O_m^G(U,C)$ with the following constraints.

$$O_m^G(U,C)=\sum_{i=1}^{c}\sum_{j=1}^{n}U_{ij}^{m}(1-K(x_j,C_i))+\sum_{i=1}^{c}\sum_{j=1}^{n}\eta_i U_{ij}^{m}(1-K(\bar{x}_j,C_i)) \tag{9}$$

where $K(x_j,C_i)=\exp(-\|x_j-C_i\|^2/\sigma^2)$, $\bar{x}_j$ is the mean of the neighbor pixels, σ^2 is the variance of the total image.

$$C_i=\frac{\sum_{j=1}^{n}U_{ij}^{m}\left(K(x_j,C_i)x_j+\eta_i K(\bar{x}_j,C_i)\vec{x}_j\right)}{\sum_{j=1}^{n}U_{ij}^{m}\left(K(x_j,C_i)+\eta_i K(\bar{x}_j,C_i)\right)};\ i=1,2,....C \tag{10}$$

$$U_{ij}=\frac{\left((1-K(x_j,C_i))+\eta_i(1-K(\bar{x}_j,C_i))\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left((1-K(x_j,C_i))+\eta_i(1-K(\bar{x}_j,C_i))\right)^{-1/(m-1)}};\quad \begin{matrix} i=1,2,....C \\ j=1,2,..,n \end{matrix} \tag{11}$$

D. *Integration of Hyperbolic Tangent and Gaussian Kernels for FCM (HGFCM)*

The ideas which are presented in HTFCM [23] and GKFCM [21] are motivated us to propose the HGFCM_S1 and HGFCM_S2. The considered hyperbolic tangent function [23] is given bellow.

$$H(x_j,C_i)=1-tanh(-\|x_j-C_i\|^2/\sigma^2) \tag{12}$$

where, σ^2 is the user defined function.

The performance of the segmentation algorithm varies with the σ^2 values. Hence, it is need to fix the appropriate value for σ^2.

In this paper, we consider the value of σ^2 with the variance of the surrounding P neighbors of radius R form the center pixel x_j.

$$\sigma^2=\sum_{j=1}^{P}\left\|x_j-\bar{x}\right\|\Big/P \tag{13}$$

where, $\bar{x}=\sum_{j=1}^{P}x_j\Big/P$.

The objective function which is used in this paper for HGFCM_S1 and HGFCM_S2 is given bellow.

where, $\bar{x}_j$ is the mean for HGFCM_S1 and median for HGFCM_S2.

$$O_m^H(U,C)=\sum_{i=1}^{c}\sum_{j=1}^{n}U_{ij}^{m}\left(1-H(x_j,C_i)\right)\left(1-K(x_j,C_i)\right)+\sum_{i=1}^{c}\sum_{j=1}^{n}\eta_i U_{ij}^{m}\left(1-H(\bar{x}_j,C_i)\right)\left(1-K(\bar{x}_j,C_i)\right) \tag{14}$$

$$U_{ij}=\frac{\left(\left(1-H(x_j,C_i)\right)\left(1-K(x_j,C_i)\right)+\eta_i\left(1-H(\bar{x}_j,C_i)\right)\left(1-K(\bar{x}_j,C_i)\right)\right)^{-1/(m-1)}}{\sum_{k=1}^{c}\left(\left(1-H(x_j,C_i)\right)\left(1-K(x_j,C_i)\right)+\eta_i\left(1-H(\bar{x}_j,C_i)\right)\left(1-K(\bar{x}_j,C_i)\right)\right)^{-1/(m-1)}};\quad \begin{matrix} i=1,2,....C \\ j=1,2,..,n \end{matrix} \tag{15}$$

$$C_i=\frac{\sum_{j=1}^{n}U_{ij}^{m}\left(K(x_j,C_i)H(x_j,C_i)\,x_j+\eta_i\,K(\bar{x}_j,C_i)H(\bar{x}_j,C_i)\,\bar{x}_j\right)}{\sum_{j=1}^{n}U_{ij}^{m}\left(K(\bar{x}_j,C_i)H(\bar{x}_j,C_i)+\eta_i\,K(\bar{x}_j,C_i)H(\bar{x}_j,C_i)\right)};\ i=1,2,....C \tag{16}$$

$$\eta_i=\frac{\min_{i'\neq i}\left(1-H(C_{i'},C_i)\right)\left(1-K(C_{i'},C_i)\right)}{\max_{k}\left(1-H(C_k,C_{\bar{x}})\right)\left(1-K(C_k,C_{\bar{x}})\right)};i=1,2,....C \tag{17}$$

HGFCM Algorithm

Input: Raw image; Output: Segmented image;

- Randomly initialize the cluster centers C_i ($c=3$ clusters)

- Membership values calculation using Eq. (14).
- Cluster centers updating using Eq. (15).
- The iterative process starts:

1. Membership values updating U_{ij} using Eq. (14).
2. Update the cluster centers C_i by using Eq. (15).
3. If $|C_{new} - C_{old}| > \xi$; ($\xi = 0.001$) then go to step1
4. Else stop

- Assign each pixel to a specific cluster for which the membership value is maximal

3. Evaluation Measures and Dataset

A *Silhouette value*

These silhouette average values measures the degree of confidence in the clustering assignment of a particular observation, with well-clustered observations having values near 1 and poorly clustered observations having values near −1. The silhouette accuracy *s(i)* of the object i is derived by the equation $s(i) = \frac{v(i) - w(i)}{\max\{v(i), w(i)\}}$. For each object we denote by the cluster to which it belongs, and compute

$$v(i) = \frac{1}{|G|} - \sum_{j \in A, i \neq j} d(i, j) \quad (18)$$

The equation *v(i)* is the average distance between the i^{th} data and all other objects in the cluster G. Now consider a second cluster **H** different from **G** and put

$d(i,H) = \frac{1}{H} \sum_{j \in H} d(i, j) =$ *average dissimilarity of:i to all objects of H and H≠G*:

B V_{pc} *and* V_{pe}

Two types of cluster validity functions, fuzzy partition and feature structure, are often used to evaluate the performance of clustering. The representative functions for the fuzzy partition are partition coefficient V_{pc} [26] and partition entropy V_{pe} [27]. They are defined as:

$$V_{pc} = \frac{1}{n} \sum_{1=1}^{c} \sum_{j=1}^{n} u_{ij}^2 \quad (19)$$

$$V_{pe} = \frac{-1}{n} \sum_{1=1}^{c} \sum_{j=1}^{n} u_{ij} \log(u_{ij}) \quad (20)$$

TABLE I: MRI DATA ACQUISITION DETAILS [26]

Sequence	MP-RAGE
TR (msec)	9.7
TE (msec)	4.0
Flip angle (o)	10
TI (msec)	20
TD (msec)	200
Orientation	Sagittal
Thickness, gap (mm)	1.25, 0
Resolution (pixels)	176×208

E. *MRI Dataset*

The Open Access Series of Imaging Studies (OASIS) [26] is a series of magnetic resonance imaging (MRI) dataset that is publicly available for study and analysis. This dataset consists of a cross-sectional collection of 421 subjects aged 18 to 96 years. The MRI acquisition details are given in Table 1. The performance of the proposed method is measures in terms of score, number of iterations and execution time. Fig. 1 illustrates two sample images selected for experimentation.

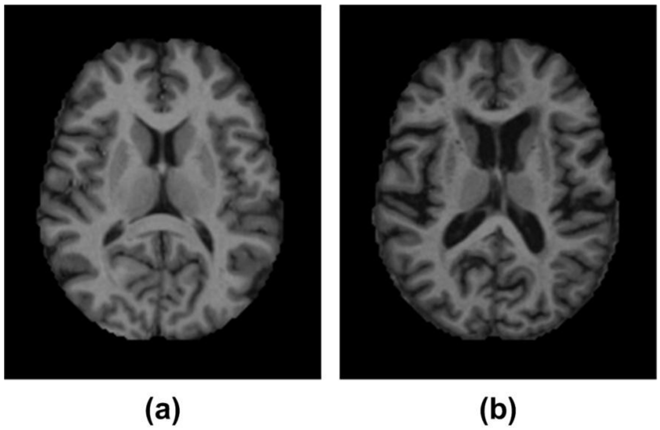

Fig. 1: Sample images used for experiments

4. Experimental Results and Discussion

In order to prove the effectiveness of the proposed algorithm, experiments were conducted on two brain MRIs [28]. The performance of the proposed algorithm is tested in terms of score, number of iterations (NI) and computational time (CT) as compared to other existing FCM varient methods on OASIS-MRI dataset.

TABLE II: EVALUATION OF VARIOUS METHODS IN TERMS OF V_{PC} WITH 10% GAUSSIAN NOISE

Method	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6	Image 7
GKFCM_S1	0.32	0.41	0.61	0.48	0.39	0.51	0.87
GKFCM_S2	0.41	0.39	0.56	0.51	0.61	0.55	0.88
HTFCM	0.46	0.48	0.66	0.67	0.66	0.66	0.79
HGFCM_S1	0.81	0.79	0.71	0.76	0.69	0.74	0.91
HGFCM_S2	0.83	0.69	0.77	0.81	0.71	0.79	0.94

TABLE III: EVALUATION OF VARIOUS METHODS IN TERMS V_{PE} WITH 10% GAUSSIAN NOISE

Noise level	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6	Image 7
GKFCM_S1	0.51	0.61	0.41	0.77	0.29	0.41	0.22
GKFCM_S2	0.48	0.52	0.35	0.61	0.15	0.22	0.14
HTFCM	0.31	0.33	0.29	0.21	0.12	0.31	0.08
HGFCM_S1	0.15	0.21	0.15	0.11	0.09	0.09	0.05
HGFCM_S2	0.14	0.16	0.12	0.05	0.06	0.08	0.02

TABLE IV: EVALUATION OF VARIOUS METHODS IN TERMS OF SILHOUETTE VALUE WITH 10% GAUSSIAN NOISE

Noise level	Image 1	Image 2	Image 3	Image 4	Image 5	Image 6	Image 7
GKFCM_S1	0.48	0.49	0.70	0.53	0.48	0.66	0.85
GKFCM_S2	0.54	0.46	0.64	0.64	0.80	0.60	0.98
HTFCM	0.52	0.63	0.78	0.80	0.72	0.76	0.81
HGFCM_S1	0.95	0.94	0.85	0.79	0.80	0.87	0.93
HGFCM_S2	0.83	0.72	0.92	0.83	0.75	0.96	0.99

Fig. 2 illustrates the cluster segmentation results of the proposed method and other existing methods with the 5% Gaussian noise on Image (a) of OASIS-MRI dataset. The performance of the proposed methods (HGFCM_S1 and HGFCM_S2) is compared with the GKFCM_S1, GKFCM_S2 and HTFCM. Tables II to IV show the segmentation performance in terms of V_{pc}, V_{pe} and Silhouette Value on sample images under Gaussian noise conditions. From, Fig. 2 and Tables II to IV, it is clear that the proposed method outperforms the other existing algorithms in terms of their evaluation measures.

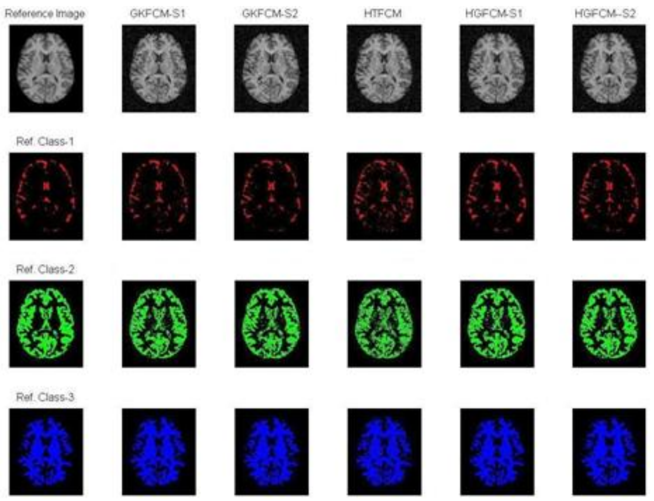

Fig. 2: Comparison of proposed methods (HGFCM_S1 and HGFCM_S2) with other existing methods (GKFCM_S1, GKFCM_S2 and HTFCM) in terms of three segmented clusters. The original image (*Image (a)*) are corrupted with 5% of Gaussian noise.

Conclusion

In this paper, a new image segmentation algorithms (HGFCM_S1 and HGFCM_S2) which are increasing the performance and decreasing the computational complexity is proposed. The algorithm utilizes the integrated hyperbolic tangent function and Gaussian kernels with spatial information. The proposed algorithm is applied on brain MRI which degraded by Gaussian noise. The segmentation results demonstrate that the proposed algorithm shows the robustness under different noises as compared to other existing image segmentation algorithms from FCM family.

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