Australian Journal of Basic and Applied Sciences, 9(1) January 2015, Pages: 250-257

AENSI Journals

Australian Journal of Basic and Applied Sciences

ISSN:1991-8178

Journal home page: www.ajbasweb.com

SFLA Optimization Based Spatial Kernel Fuzzy C-Means Clustering for MRI Image Segmentation using SIFT Descriptors

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ARTICLE INFO

Article history:
Received 19 September 2014
Received in revised form
19 November 2014
Accepted 22 December 2014
Available online 2 January 2015

Keywords:
Fuzzy c-means algorithm (FCM), Shuffled Frog Leap Algorithm (SFLA), image segmentation, SIFT descriptors, post segmentation.

ABSTRACT

In this paper, we propose an enhanced fuzzy c-means clustering process for image segmentation. This algorithm plays important role in image segmentation to achieve better segmentation results. Here, (FCM) fuzzy c-means algorithm performances are increased using SFLA algorithm and SIFT descriptors. Shuffled Frog Leap Algorithm provide the better initial optimization and SIFT feature descriptors reduce the false boundaries by non-boundary image features.PSO algorithm provides fast segmentation more than SFLA however it is effortlessly falls in local optimization, these lead false boundaries in image segmentation, and this has overcome using SFLA to attain global optimization. In which, image is processed in three stages. In first stage, fuzzy c-means algorithm and optimization as attained. In second stage SIFT descriptors used to reduce the false boundaries, in final stage reordering of possibly misclassified pixels in image. Our proposed method, shuffled frog leaf based spatial Kernel fuzzy c-means (SFKFCMS) was evaluated with various FCM based algorithms and tested in numerous test images. This method provides better efficiency and optimized results in image segmentation.

To Cite This Article: Somasundaram Devaraj, SFLA Optimization Based Spatial Kernel Fuzzy C-Means Clustering for MRI Image Segmentation using SIFT Descriptors. ***Aust. J. Basic & Appl. Sci.,*** *9(1): 250-257, 2015*

INTRODUCTION

Image segmentation is the most important progression in image analysis and processing. Primarily segmentation outcomes affect all the subsequent methods of image analysis such as object representation and description, feature measurement, and even the following higher level tasks such as object classification. Hence, image segmentation is the most essential and essential process for enabling the description, classification, and visualization of regions of interest in any medical image (Papari *et al* 2011). Normally segmentation categories based on thresholding, region grow, entropy based edge detection, etc., beyond this methods, the statistical methods are used to segment medical images such as maximum likelihood method ,etc., these MLC algorithm merged with neural network classifiers and genetic algorithm techniques used to increase the segmentation accuracy.

In certain conditions, probability supervised used for 3-D medical images. So many methods are newly developed for image segmentation algorithms such as SOM based image segmentation (Andres Oritz *et al*, 2011), Fuzzy clustering based segmentation (Megha P *et al* , 2011). In our work we concentrate on fuzzy clustering algorithm. In this each pixels assigned with each data point to each region clusters respective to the membership functions to attain better image quality. Initially Zadeh introduced fuzzy sets for image segmentation (Zadeh.L , 1965) and this as further developed by Bezdek ,1981 provided a methodology for fuzzy c-means clustering algorithm (Kang J *et al* 2009). Compare to the newer method of segmentation to the conventional fuzzy provide inefficient results. Because of it is noise sensitivity and process depends only the pixel intensities. This has improved using the special information to adopt the special constraints and each pixel in the image coordinates with nearest region.

Standard Fuzzy C-means applied to the gray level images by Ahmed *et al* (Izakian *et al* 2011). This algorithm had high computational time and no of iteration as more. This has resolved using two variants system as FCM-S1 and FCM-S2 given by Chen and zhang (2004). This method improved based on weighted histogram as EnFCM by Szilagyi *et al* (2003). Segmentation method further developed as IFCMS (saric *et al*, 1995) discussed for post segmentation adjustment in image segmentation.

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In IFCMS, the PSO algorithm as used for initialization and mahalanobis distance statistical distance as used instead of Euclidian distance. In our method, SFLA algorithm is used to initialization and SIFT descriptors are used to extract the statistical feature from image. The paper is organised as follows. In section 2 describe the Kernel fuzzy c-means in segmentation. In section 3 discuss the proposed image segmentation method. In section 4 discussed experimental results and various algorithm comparisons. In section 5 provide the conclusion and further development of this algorithm.

Kernel Fuzzy C-means in image Segmentation:

The Kernel Fuzzy C-means algorithm is applied to medical images for its best separate from the foreground objects from the background. The important benefit of kernel functions is that the objects in the image can be analysed in the high dimensional feature space instead of the input data space. By using this method, the data element in the high dimensional feature space are divided into C fuzzy clusters and a matrix function X is obtained. It is obtained from the following function.

$$J(X,Y) = \sum_{a-1}^{c} \sum_{b-1}^{n} x_{ab}^{m} \left(\emptyset(u_a) - \emptyset(y_a)\right)^2 \quad (1)$$

Where,

$$\left(\emptyset(u_a) - \varphi(y_b)\right)^2 = K(u_b, u_b) + K(y_a, y_a) - 2(u_b, y_a) \quad (2)$$

The inner product of the kernel function is given as

$$K(x,y) = \emptyset(x^T)\emptyset(y) \quad (3)$$

According to the above equations, the equation (1) can be rewritten as,

$$J(X,Y) = 2\sum_{a-1}^{c} \sum_{b-1}^{n} x_{ab}^{m} \left(1 - k(u_b, y_a)\right) \quad (4)$$

$$x_{ab} = \frac{(1/(1-k(u_b,y_a)))^{1/(m-1)}}{\sum_{k=1}^{n}(1/(1-k(u_b,y_a)))^{1/(m-1)}} \quad (5)$$

$$y_a = \frac{\sum_{k=1}^{n} x_{ab} k(u_b, y_a) u_b}{\sum_{k=1}^{n} x_{ab}^{m} k(u_b, y_a)} \quad (6)$$

For straight forwardness of the function, the Gaussian function is utilized. By using kernel functions additionally, the Eq. (5) and (6) are modified. The Eq. (3) is analysed by using the following function:

$$d(x,y) = \sqrt{2(1 - k(x,y))} \quad (7)$$

Where $d(x,y)$ in Eq. (7) is a metric in the original space and $k(x,y)$ is the Gaussian kernel function. The data point u_b is capable with an additional weight which measures the similarity between u_b and y_a and when u_b is outliner.

Proposed method:

Our method consists of three steps for image segmentation.

1. Initialization of the classification of pixels using SFLA algorithm for attaining the initial set of clusters in centre of image.
2. Segmentation of the image using the SIFT descriptors.

Each Step as explained below,

KFCM initialization using Shuffled Frog leap Algorithm (SFLA):

The Shuffled Frog Leaping Algorithm (SFLA) is a biological evolutionary algorithm based on swarm intelligence, was proposed by Eusuff and Lansey in (2003),(Aijun Zhua *et al*, 2012),(Bong *et al* ,2012). SFLA begin with an initial population of 'N' frog.

$P = \{X_1, X_2,..,X_N\}$ (8)

Which are randomly with in the feasible space Ω.

For the position of the i^{th} frog is represented for mxn dimension,

$X_i = [x_{i1}, x_{i2}...x_{im}]^T$ (9)

$Y_j = [y_{j1}, y_{j2}, y_{j3},...y_{jn}]^T$ (10)

In this to evaluate the frog's position, a fitness function is defined. The frogs are sorted in a descending order depends upon the fitness function. The entire population is divided into m memeplexes, each of which consisting of n frogs i.e., N = n x m. within each memeplexes , the position of frog i^{th} (D_i) is adjusted depend upon the difference between the frogs one by one in order between the m existing memeplexes.

Position change (F_j) = rand ( ) x (X_b-X_w) (11)

X_w (new) = X_w+ F, ($F< F_{max}$) (12)

Where,

X_b - Best fitness

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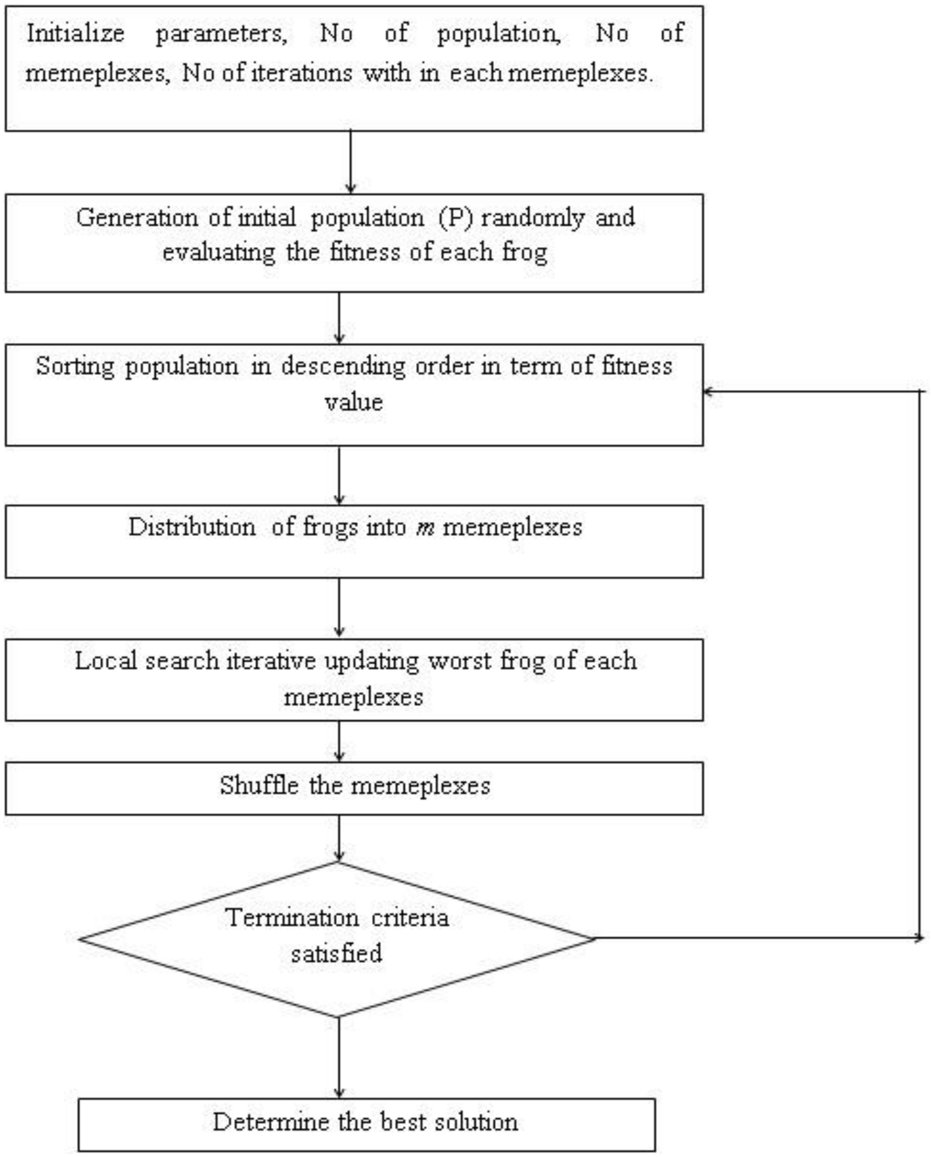
X_w – worst fitness
rand () – random number in the range of [0, 1]
For each sub group of region fitness function and updating local optimal solution as,

$$S = \begin{cases} \min \{int(rand(U_B - U_W)).S_{max}\} for (U_B - U_W \geq 0) \\ \max \{int(rand(U_B - U_W)).-S_{max}\} for (U_B - U_W \leq 0) \end{cases} \quad (13)$$

Flow chart for SFLA algorithm,



Segmentation Algorithm:

In image segmentation central coordination of image affected by strong edges adjacent to the true boundaries. Subsequently, SIFT feature is used to solve a difference of Gaussian pyramid Δ is computed to get the gradient magnitude and orientation for each point of the image. $\Delta(x,y,\sigma)$ is computed by,

$$\Delta(x, y,\sigma) = (G (x, y, k \sigma) - G(x, y, \sigma)) * I (x, y) \quad (14)$$

$$= L (x, y, k \sigma) – L (x, y, \sigma) \quad (15)$$

Where,
$\Delta(x, y,\sigma)$ - variable scale Gaussian Function.
I(x, y) – input image.
L (x, y, σ) – scale space of an image.
Let x_i is the contour point and n_i is the corresponding normal direction.

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For each boundary region x_i, sample k points used for spacing δ evenly from both sides in normal direction. The location of j^{th} pixel is

$$x_i^j = x_i + j.\,\delta.n_i \tag{16}$$

In which f_j denote the modified SIFT feature of x_i^j, then

$$g(x_i) = (f_1, f_2 \ldots f_k) \tag{17}$$

Computing the consistency for each region as,

$$C_i = \frac{L}{\sum_{l=1}^{L} \sigma(l)} \tag{18}$$

The SIFT approach (Plinio *et al*, 2009), for an image feature generation, takes an image and transforms it into a "large collection of local feature vectors". Each of these feature vectors is invariant to any scaling, rotation or translation of the image. This approach shares many features with neuron responses in primate vision.

To aid the extraction of these features the SIFT algorithm applies a 4 stage filtering approach: Scale-Space Extrema Detection, Keypoint Localization, Orientation Assignment, and Keypoint Descriptor. This stage of the filtering attempts to identify those locations and scales those are identifiable from different views of the same object. This can be efficiently achieved using a "scale space" function. Further it has been shown under reasonable assumptions it must be based on the Gaussian function. The scale space is defined by the function

$$L(x, y,\sigma)=G(x, y,\sigma)*I(x, y) \tag{19}$$

Where * is the convolution operator, G (x, y, σ) is a variable-scale Gaussian and I (x, y) is the input image. Various techniques can then be used to detect stable Keypoint locations in the scale-space. Difference of Gaussians is one such technique, locating scale-space extrema, D (x, y, σ) by computing the difference between two images, one with scale k times the other.

To detect the local maxima and minima of D (x, y, σ) each point is compared with its 8 neighbours at the same scale, and its 9 neighbours up and down one scale. This stage attempts to eliminate more points from the list of key points by finding those that have low contrast or are poorly localized on an edge. This is achieved by calculating the Laplacian, value for each Keypoint found in stage 1.

The location of extreme, Z, is given by:

$$Z = -\frac{\partial^2 D^{-1}}{\partial x^2}\ \frac{\partial D}{\partial x} \tag{20}$$

If the function value of Z is below a threshold value then this point is excluded. This removes extrema with low contrast. To eliminate extrema based on poor localization it is noted that in these cases there is a large principle curvature across the edge but a small curvature in the perpendicular direction in the difference of Gaussian function. If this difference is below the ratio of largest to smallest eigenvector, from the 2x2 Hessian matrixes at the location and scale of the Keypoint, the Keypoint is rejected.

Orientation Assignment:

This step aims to assign a consistent orientation to the key points based on local image properties. The Keypoint descriptor, described below, can then be represented relative to this orientation, achieving invariance to rotation. Use the key points scale to select the Gaussian smoothed image L, and Compute gradient magnitude, m

$$m(x,y) = \sqrt{\left(L(x+1,y) - L(x-1,y)\right)^2\left(L(x,y+1) - L(x,y-1)\right)^2} \tag{21}$$

Compute orientation, θ

$$\theta(x,y) = \frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)} \tag{22}$$

Form an orientation histogram from gradient orientations of sample points. Locate the highest peak in the histogram [5]. Use this peak and any other local peak within 80% of the height of this peak to create a Keypoint with that orientation.

Key point Descriptor:

The local gradient data, used above, is also used to create Keypoint descriptors. The gradient information is rotated to line up with the orientation of the Keypoint and then weighted by a Gaussian with variance of 1.5 * Keypoint scale. This data is then used to create a set of histograms over a window centered on the Keypoint. Keypoint descriptors typically use a set of 16 histograms, aligned in a 4x4 grid, each with 8 orientation bins, one for each of the main compass directions and one for each of the midpoints of these directions. This result in a feature vector containing 128 elements. These resulting vectors are known as SIFT keys and are used in a nearest-neighbours approach to identify possible objects in an image.

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Post segmentation:

In the high noise density images the segmentation not attains properly due to the classification errors and this has to be reduced to refine the segmentation . These errors lead incorrect boundary shapes, local distortions in the regular contours and stray pixels in the similar areas of the image. This alteration of possibly misclassified pixels takes place in two steps. Initially the detection of misclassified pixels in image by removing all pixels that do not have the same label in their 3X3 region (N_{ns}).This as reclassified of removed pixels by reducing similar measure using local information in 5X5 region (N_{rl}) of each removed pixel in the original image.

$$J_i = \frac{\alpha\sigma_j^{(i)} + \|x_i - u_j^{(i)}\|}{\beta N_j} + \sum_{k=1, k\neq j}^{N_{pi}} \sigma_k^{(i)} \quad (23)$$

Where,

N_{pi} – is the number of different labels present in N_{rl} neighbourhood of the pixel i.

N_j - is the number of pixels belonging to the cluster j in N_{rl} neighbourhood of the pixel i.

x_i –is the extracted pixel to be reclassified.

$u_j^{(i)}$ - is the local mean of the class j in N_{rl} neighbourhood

$\sigma_j^{(i)}$ - is the local variance of the cluster j in the N_{rl} neighbourhood of the pixel x_i after its reallocation to this cluster.

$\sigma_k^{(i)}$ - is the local variance of the cluster k in the neighbourhood of the pixel x_i.

α- adjust the impact of the local variance on the reallocation of pixels set as 0.65

β – is the fixed parameter which determines the impact of the number of pixels belonging to the cluster j. This parameter is set to β N_j represents the proportion of the cluster j in the local neighbourhood of the pixel to be reclassified.

Thus the extracted pixel x_i is reallocated to the class j that minimizes the objective function J_i (J= argmin (J_i)).

Experimental results:

In the Proposed method implemented in MATLAB version 2012, Segmentation accuracy (SA) as measured for previous FCM Segmentation models. Various methods applied for MRI Brain images and synthetic images such as FCM, FCM-S1, FCM –S2, EnFCM and IFCMS and performance is visualised and measured parameter as tabulated in table 1.

$$SA = \sum_{i=1}^{c} \frac{card(A_i \cap C_i)}{\sum_{j=1}^{c} card(C_j)} \quad (24)$$

Results analysis on MRI Brain image:

The quantitative measure on MRI brain image as analysed from artificially simulated and noise added images. The performance of different segmentation methods are compared the availability of the ground truth of segmentation. Simulated MRI images taken in T1 mode with slice thickness of 1 mm. image as noised with 4%, 6% and 9%, and the non-parameter was set to 0%, 25%, and 50% for each noise level. Figure shows the visualised segmentation results. Table 1 shows the Segmentation accuracy of the various algorithms and its global average. Analysed results shows that the proposed methods provide better results compare to other methods.

(a)Original image

(b) Ground truth images

(c) FCM segmentation

(d) FCM S1 segmentation

(e) EnFCM segmentation

(f) IFCMS segmentation

(g) SFKFCMS segmentation

Figure 1: Segmentation Results of simulated Brain MRI image.

Table 3: Comparisons of Average segmentation accuracy (SA %) for various methods

Figure 2:Comparision of Segmentation Accuracy for simulated MRI brain images

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Figure captions:

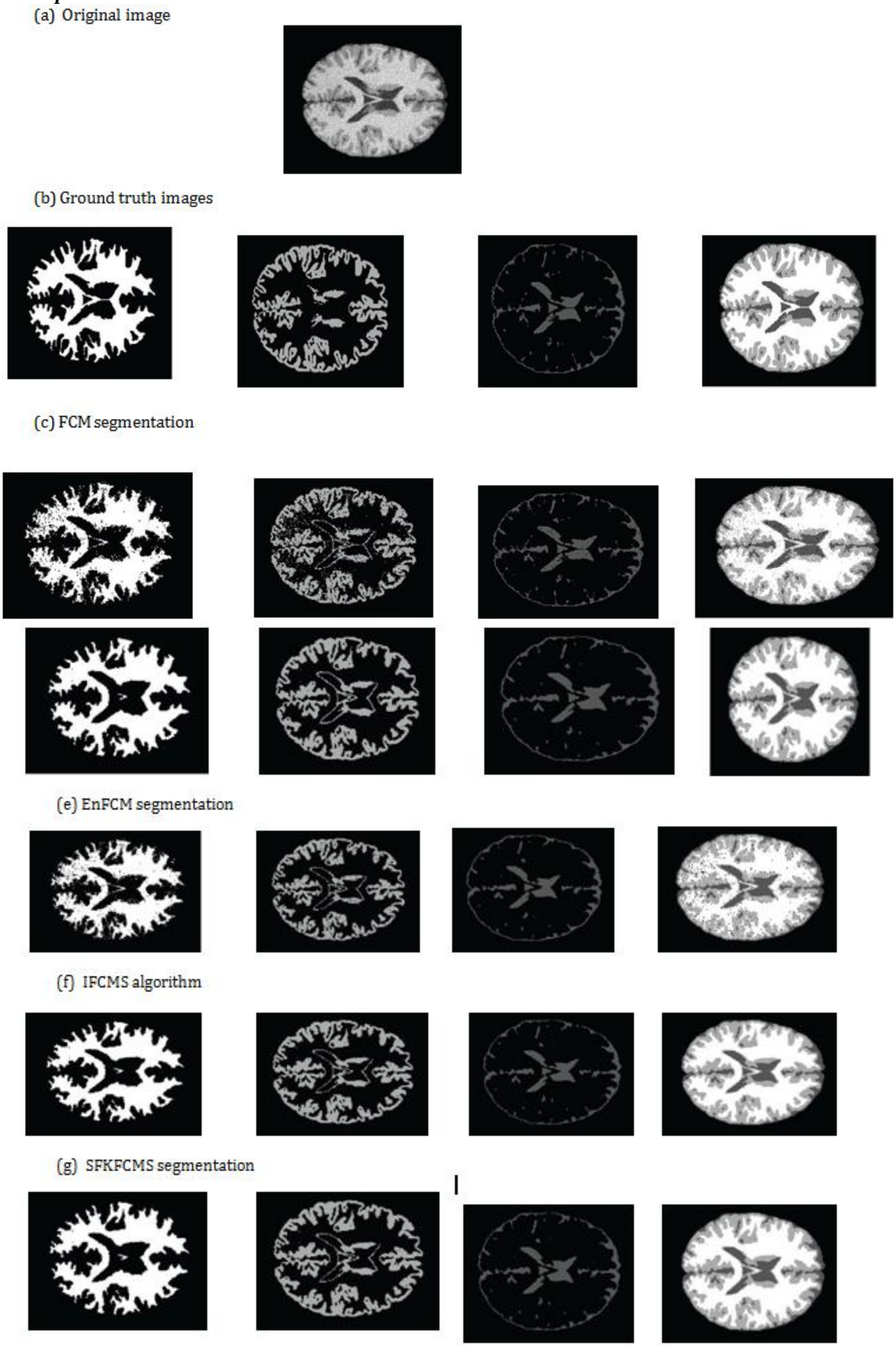

Fig. 1: Segmentation Results of simulated Brain MRI image.

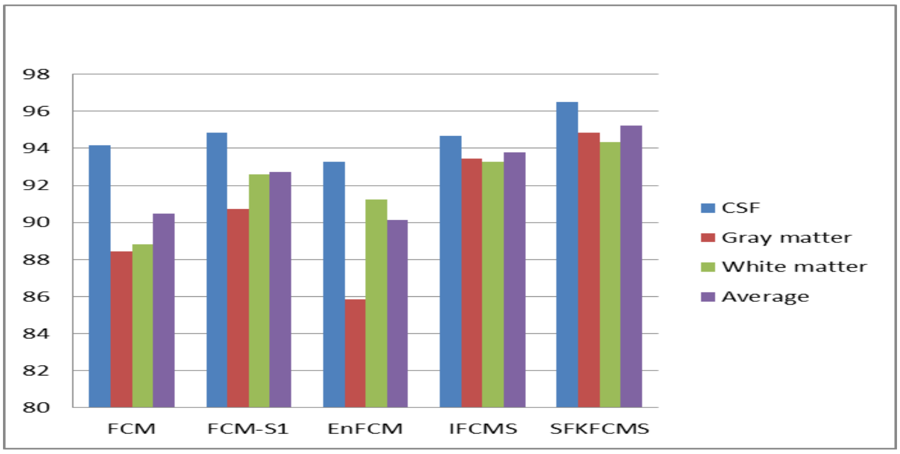

Fig. 2: Comparision of Segmentation Accuracy for simulated MRI brain images.

Table captions:

Table 1: Segmentation accuracy comparison of various methods in different noise.

	FCM	FCM-S1	En-FCM	IFCMS	SFKFCMS
Gaussian noise	46.50	87.34	78.65	92.52	95.57
Uniform noise	43.41	82.10	73.61	94.31	97.32
Salt and pepper noise	75.81	82.04	80.11	91.80	94.11

Table 2: Segmentation Accuracy of various methods with different noise density.

	FCM	FCM-S1	En-FCM	IFCMS	SFKFCMS
2 clusters	91.06	96.42	99.85	99.81	99.92
3 clusters	65.41	81.30	84.50	94.28	97.34
4 clusters	38.18	79.65	78.68	93.46	96.47
5 clusters	26.42	75.67	58.68	85.11	90.51

Table 3: Comparisons of Average segmentation accuracy (SA %) for various methods.

	FCM	FCM-S1	EnFCM	IFCMS	SFKFCMS
CSF	94.15	94.85	93.26	94.68	96.51
Gray matter	88.45	90.72	85.87	93.43	94.85
White matter	88.81	92.58	91.23	93.28	94.35
Average	90.47	92.72	90.12	93.79	95.24

Conclusion:

In this paper, SFKFCMs algorithm applied to improve the segmentation accuracy. The improvement is attained using the SFLA algorithm to avoid the local minima. The classification is improved using the SIFT descriptors. The post segmentation is used to refine the misclassified pixels in the image. The proposed method is compared with the various FCM methods and applied to the MRI Brain images. Performance of the method tested with various noises and different noise levels. In the occurrence of high density noise some pixels located at boundaries between two adjacent regions are misclassified. This has reduced using the global minimum and post segmentation method. Image Segmentation Experimental results shows that the proposed method is more efficient than other methods.

ACKNOWLEDGEMENT

Author is thankful to Er. R.Thiruvengada Ramanuja Doss, Chairman of Sri vidya groups, Virudhunagar and Dr.S.Sankaralingam, Principal of SVCET for providing the necessary facilities for the preparation of this paper.

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