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An Efficient Approach in Image Segmentation based on Energetic Self Organizing Map

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***Abstract*—Image Segmentation is one of the key problems in Digital Image Processing which acts as a Pre-processing for major image related tasks. The lack of segmentation accuracy is the chief drawback of the existing methods and this paper proposes a novel image segmentation method to perform generic image segmentation that is united to the three types of images namely Natural, Medical and Satellite. This new method is named as Image Segmentation using Energetic SOM. First the input image is denoised by a novel image denoising scheme namely 'Adaptive Window based Switching Fuzzy denoising' (AWSFD). After that the noise free image is preprocessed by a new Background Optimization method namely Dynamic Adaptive Threshold based Background Optimization method (DATBO). The pre-processed image is undergone process clustering process by using the novel 'Fuzzy Octagon Window Local Information C Means' (FOWLICM) Method' to optimize the feature vectors. Finally the novel Energetic Self Organizing Map (SOM) method segments the noise-free image. The proposed method outperforms the existing methods with significant excellence in the parameter segmentation-accuracy.**

Index Terms: **AWSFD, DATBO, FOWLICM, ESOM, Image Segmentation, Clustering.**

1. Introduction

Image Segmentation is a basic step to slice an image into meaningful non Overlapping groups depends on extracted image features [1]. Image segmentation which is a midlevel computer vision issue can be used as a pre-processing task to point towards object recognition and image classification [2]. Images can be classified into three major categories viz. Natural, Medical, and Satellite images. The Natural image Segmentation plays a significant role to identify Natural objects from natural scientist [3]. Medical image segmentation helps physiologists to quantity and assessment of image data which assists pre-planning of treatments [4]. Satellite image segmentation induces the astrological scientists to invent new galaxies and plants [5]. The Segmentation accuracy of the existing methods is still inadequate upon the current world scenario. So, there is a necessity of designing new approaches related with high accuracy generic image segmentation.

II. Literature Survey

The Author Joridi Pont-Tuset et al. [6] put forth a natural image segmentation scheme based on multiscale combinational grouping. The past execution is the advantage of this method. Huazhu Fu, et al. [7] suggested a object based multiple foreground segmentation scheme for natural scene segmentation. The highly textured images produce false segmentation using these methods. Kashif Hussain Memon et al. [8] designed a clustering algorithm for natural images using generalized fuzzy C-means clustering algorithm which mitigates de-merits of traditional FCM (Fuzzy C-Means). Jia-Hao Syu et al.[9] developed a natural image segmentation based on iterative contraction and merging. The availability of plenty of boundary is the advantage of this method while the demerit is the hard thresholds. Jianbing Shen et al. [10] authored natural image segmentation with the help of higher order energies. The fast convergence is the advantage while the non robustness of the noisy environment is the demerits of this method. Xiang Wang et al. [11] report natural image segmentation based on salient object detection which is influenced by multiscale contextual neural network. The advantage is the edge preservation while the disadvantage is the fainted segmentation on the context of multi object scenario.

Alaa Khadidos et al. [12] expressed a medical image segmentation based on weighted level set method. The accurate boundary detection is the advantage of this method. The author Hougli Lv et al. [13] delivers a active contour segmentation scheme to segment vessel images to mask vascular lesions. The core concept involves here in the fractional order differentiation and fuzzy energy. The advantage of this work is that it is robust to initial contour. The author Sharmin Sultana et al. [14] draws a method to segment the cranial nerves using discrete deformable 3-D contour and surface models. The complexity overhead is the demerit of that work. Mahdi Massousi et al. [15] defines a kidney segmentation technique for Medical images categorized with three layers ultra sound images. This work

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introduces a complex valued implicit shape model to form the 3-D kidney shape. The advantage of the cost effective segmentation and the disadvantage is the fainted robustness against inhomogeneous regions.

The paper [16] carry out a Liver CT-image segmentation method causes by Active Contour concept. The key algorithm is Convolutional Neural Network (CNN) and it drives the advantage on Robustness against low contrast and heterogeneous lesions. This is a semi automatic technique because of the absence of lesion detection.

Rocco Restaino et al. [17] concentrate satellite image segmentation through context adoptive path sharpening technique. The Quickbird and the WorldView databases are utilized to reach simulations. The advantage of this method is the well maintenance of accuracy and computational burden. Javier Lopez-Fandin et al. [18] forwards with a hyper spectral image segmentation by using the concept of cellular automata. The advantage is the segmentation by preserving spectral information.

Min Wang et al. [19] derive a Satellite image segmentation scheme for high resolution images by adopting region line association constraints. The disadvantage is that it handles only limited features among the abundant quantity of features. Andres Troya et al. [20] deliver a image segmentation method associated with remote sensing images. According with this concept, the aggregation of segmentation contains collaborative agents. The positive side of this method is the significant level reduction of segmentation errors. The authors Aline Canetti et al. [21] suggest a satellite image segmentation method to get wisdom on multi-temporal urban forest area by developing an intelligent tool.

The existing methods are lamented by reduced segmentation accuracy. So this paper introduces a novel method to make energetic segmentation on digital images via. Four novel algorithms and they are

- Noise reduction by Adaptive Window based Switching Fuzzy De-noising
- Pre-processing by Dynamic Adaptive Threshold based Background Optimization
- Clustering by Fuzzy Octagon Window Local Information C-Means
- Energetic Segmentation by Energetic Self Organizing Map.

The Energetic Self Organizing Map efficiently segments the image into meaningful regions.

The proposed methodology is described in section 3.The experimental results are given in section 4. The conclusion session briefs the observation in final section. In the chapter 5 the reference papers which are used in the papers are listed.

III. METHODOLOGY

This research proposes a novel method for image segmentation namely energetic image segmentation using Adaptive Window based Switching Fuzzy denoising, Dynamic Adaptive Threshold based Background Optimization method, Fuzzy Octagon Window Local Information C Means and Energetic Self Organizing Map. It comprises of four main divisions and they are:

- Noise reduction by Adaptive Window based Switching Fuzzy de-noising
- Pre-processing by Dynamic Adaptive Threshold based Background Optimization method
- Clustering by Fuzzy Octagon Window Local Information C Means
- Energetic Segmentation by Energetic Self Organize Map.

The overall architecture diagram is expressed in fig.1.

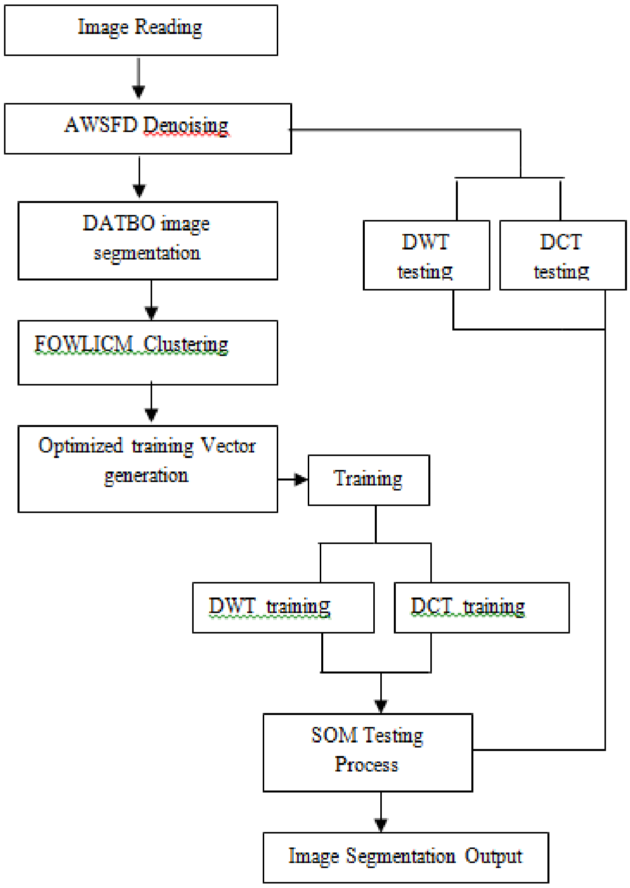

Fig.1. Block diagram of proposed method

A. Noise Reduction

The novel Adaptive Window based Switching Fuzzy De-noising noise reduction method reduces the Salt and Pepper noise of an image. The speciality of this noise reduction scheme is the noise reduction without blur artifacts over the corrected pixels. The fuzzy technique and multi window concept are the backbone of this algorithm. This method is sub-divided into 6 modules such as

- Adaptive window size deduction
- Adaptive window based Median filter

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- Absolute Luminance Difference Calculation
- Fuzzy based threshold Computation
- Fuzzy membership value Computation
- Fuzzy based restoration

The window mask dimensions are considered as 3x3 or 5x5 or 7x7 or 9x9 to perform the switching median filter. The initial window size is decided as 3x3 and the existence of any non-noisy pixel inside is found. If it is found, then the switching window size is decided as 3x3 for certain pixel p(i,j), otherwise find the matched window size until it meets a non-noisy pixel. This seeking process is progressed up to the maximum size 9x9.

The individual switching window size is maintained in program memory array. Now the elements of each pixel based on its switching window size is extracted. The window elements are sorted based on ascending way. The median value along with the sorted elements is found and used to replace the current pixel. The output is known as Adoptive window based Median filter.

A overlap window based on the pixel p(i,j) is extracted and the maximum difference value among the neighbours is computed and stored in MaxAbsLumDiffArray. The minimum difference value among the neighbourhood elements are found and stored in MinAbsLumDiffArray are found and stored in MinAbsLumDiffArray. This two parameters computation is known as Absolute Luminance Difference Calculation.

The fuzzy based thresholds T1, T2 are calculated using equation Equ.1 and Equ.2.

$$T1 - Maximum\ (MaxAbsLumDiffArray)\ x\ 0.25 \quad (1)$$

$$T2 - Minimum\ (MinAbsLumDiffArray)\ x\ 0.25 \quad (2)$$

$$T1 \quad - Lower\ limit$$

$$T2 \quad - Upper\ limit$$

The membership of dominance of noiseness is calculated using Equ.3. The parameter T1, T2 and MaxAbsLumDiffArray are participated to compute this task.

The membership of noisiness is computed using T1, T2 and MaxAbsLumDiffArray.

if (MaxAbsLumDiffArray (i,j) < T1)
FuzzyMembership (i,j) = 0
else if (T1 >= MaxAbsLumDiffArray (i,j) And MaxAbsLumDiffArray (i,j) < T2)
FuzzyMembership (i,j) = MaxAbsLumDiffArray (i,j) – T1) / (T2-T1)
else if (MaxAbsLumDiffArray (i,j) > = T2)
FuzzyMembership (i,j) = 1 (3)

The restored pixel is modeled by fuzzy based approach to replace the noisy pixels based on Equ.4.

The restoration process is done only for noisy pixels.

- The non-noisy pixels are leaved as it is.
- The restoration process is defined as

Restored_image (i,j) = ((1 – FuzzyMembership (i,j)) x MinAbsLumDiffArray(i,j))) +
((FuzzyMemebership (i,j) x MedianFilterImage(i,j))) (4)

In this more the noisy pixels are replaced restored pixels and the nonnoisy pixels are leaved without any change.

B. Pre_processing

The noise free image is pre-processed by the Dynamic Adoptive Threshold based Background Optimization method. The output of this method encourages the fourth coming task clustering to yield better result. This method is well explained in the paper [22]. In this method a pixel p(i,j) its window elements are extracted. The averaging process engaged with Minimum value and Maximum value decides the background threshold. The enhanced value is defined based on the Background threshold, upper limit of grey scale value, log based intensity, Window minimum value and Window maximum value. The enhanced pixel data is used as a replacement value for the pixel p(i,j).

C. Clustering

This is a novel method for image clustering to drawn out an approximate clustering which is entitled as Fuzzy Octagon Window Local Information based C-Means Method. This is an ultra modified version of the Fuzzy C-Means (FCM) method. The main parts of this method are

- Initialization Module
- Distance Computation
- Fuzzy factor computation on Octagon Window module
- Cluster head updation module

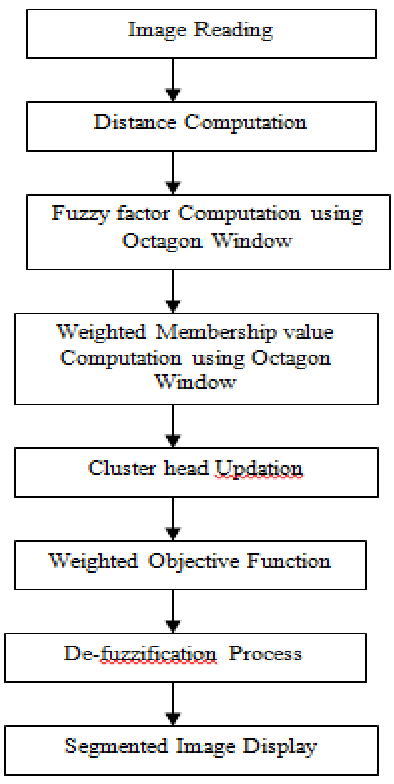

Fig. 2. Block diagram of Clustering Method.

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The fuzzy initialization process includes the membership matrix, fuzzy type, Maximum possibility of iteration, Objective function Threshold limit. The Octagon window format is decided as 5x5. The distance between the pre-processed data and cluster head is computed for the whole clusters.

Fuzzy factor computation based on the Octagon window is used to get quick convergence and fast segmentation.

Fuzzy factor computation using Octagon window The concerned pixel's intensity representation related with them weight values are given below:

P (i -2, j-1) * 0.05
P (i -2, j+1) * 0.05
P (i -1, j-2) * 0.05
P (i -1, j+0) * 0.15
P (i -1, j+2) * 0.05
P (i +0, j-1) * 0.15
P (i +0, j+1) * 0.15
P (i +1, j-2) * 0.05
P (i +1, j+0) * 0.15
P (i +1, j+2) * 0.05
P (i +2, j-1) * 0.05
P (i +2, j+1) * 0.05

The shaped elements yield their total energy for 40%. The elements yield the total energy for 60%. The empty locations are not considered for fuzzy function computation.

The membership values are packed with the fraction of domination on each cluster for each pixel. The membership matrix computation is progressed by using Octagon window instead of square window to reduce the complexity and also to increase the execution speed. The new cluster heads are found using the new membership function. The objective function is designed to adopt with the new fuzzy factor which is tuned by Octagon shape window.

The de-fuzzification process allocates each pixel corresponding with their exact cluster index. Now the approximate clustered output is obtained.

D. Energetic segmentation by ESOM

The Energetic SOM based clustering method which is explained in [22]. The training data for ESOM is derived from the FOWLICM clustered output using an averaging process. The energy weight vector of SOM is converted into transformed domain using DWT Transform and DCT Transform. The first three elements of DWT output and the first three elements of DCT output are fused to make positive alterations for each cluster. For wavelet processing db4 haar transform is used. Both the DWT and DCT transform are applied on the 3x3 size overlapped window of each pixel.

The testing process is handled by each 3x3 size matrix extracted from noise free image. The DWT and DCT transform based features are derived for the specified 3x3 size matrix. This research introduces the consecutive neighbour based similarity measure using Absolute error distance within the neighbour length 5. The parameter Absolute error model distance is enriched by integrating √2 multiplication. The best match cluster index is assigned for the specified pixel p(i,j). Further the segmented results are refined by a three stage process. This refinement process switch over the Orphan like pixels to a appropriate cluster index.

3. Experimental Results and Analysis

The proposed method is implemented in matlab14 and analysed against the following two existing methods. They are

- Adoptive local information based fuzzy clustering for image segmentation (SEG_ALIFC) [23].
- Automated grey value estimation based image segmentation (SEG_AGVE) [24].

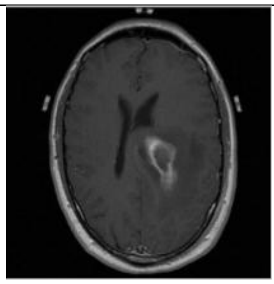
The images selected from the three data bases such as

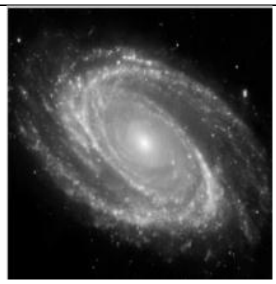
Berkely Segmentation Dataset (BSD) [25].

The Cancer Image Archive (TCIA) [26].

National Aeronautics and Space Administration (NASA) [27].


Natural image input


Medical image input


Satellite image input

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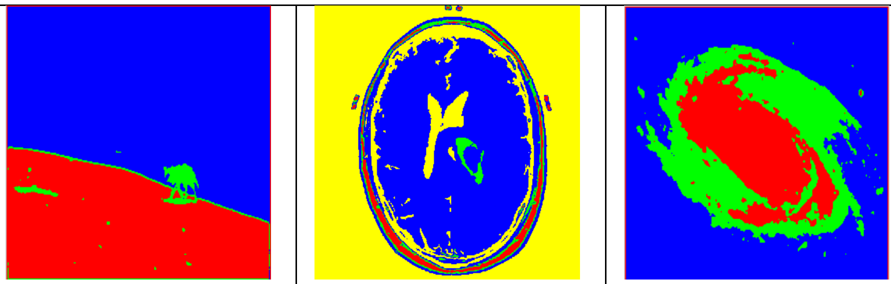

Final Segment Output | Final Segment Output | Final Segmented Output

Fig.3. Output of the proposed SEG_ADFESOM method.

Table 1. Peak Signal to Noise Ratio (PSNR) Analysis

Database Name	**Image name**	**PSNR**			
		SEG_ALIFC	**SEG_AVGE**	**SEG_NC**	**Proposed (SEG_ADFESOM)**
DB_BSD Natural Database	Fox	47.19	48.40	50.25	**54.13**
	Mountain	47.30	48.52	50.30	**54.51**
	Eagle	47.54	48.32	49.49	**53.43**
DB_TCIA Medical Database	Brain_1	49.28	50.35	52.01	**55.23**
	BloodCell	47.34	48.18	51	**54.97**
	Brain_2	47.16	48.96	51.68	**55.10**
DB_NIVL Satellite Database	Galaxy_1	47.24	48.52	49.32	**54.55**
	Galaxy_2	45.17	46.23	47.63	**52.31**
	Island	47.04	47.99	49.04	**53.48**

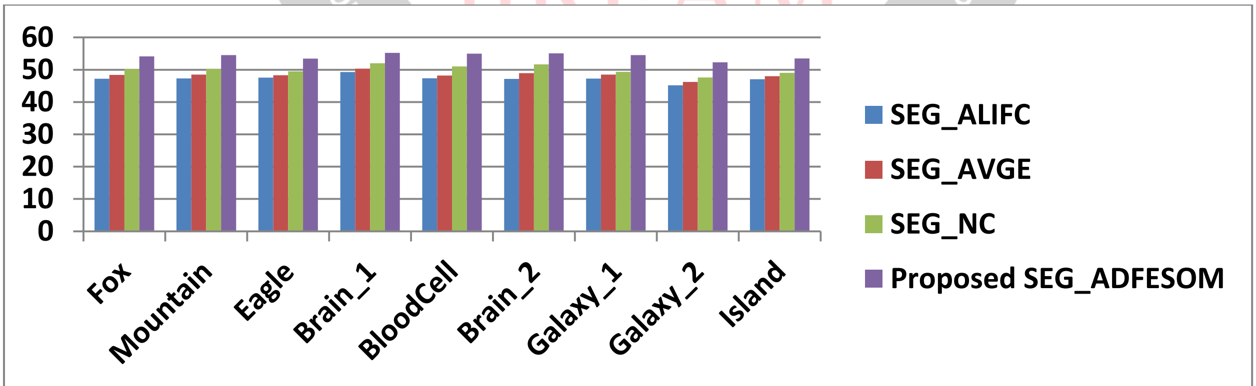

Fig.4. Peak Signal to Noise Ratio (PSNR) Chart.

In the table1 and Fig.4 we can be analyzed the proposed method holds high average PSNR compared with the previous models. The segmentation method SEG_NC is the second best method in image segmentation. In the PSNR analysis three different types of databases are analysed with the four methods. The highest proposed value is 59.47 in TCIA database.

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Table 2. Segmentation Accuracy Analysis

Database Name	Image name	Segmentation Accuracy in (%)			
		SEG_ALIFC	SEG_AVGE	SEG_NC	Proposed (SEG_AFDESOM)
DB_BSD Natural Database	Fox	81.08	83.16	86.33	92.48
	Mountain	81.27	83.36	86.42	92.61
	Eagle	81.68	83.02	85.03	91.80
DB_TCIA Medical Database	Brain_1	82.95	84.78	87.58	93.74
	BloodCell	79.69	81.13	85.88	92.56
	Brain_2	79.38	82.44	87.02	92.78
DB_NIVL Satellite Database	Galaxy_1	80.91	82.60	83.96	92.86
	Galaxy_2	76.90	78.70	81.08	89.05
	Island	80.08	81.70	83.48	91.04

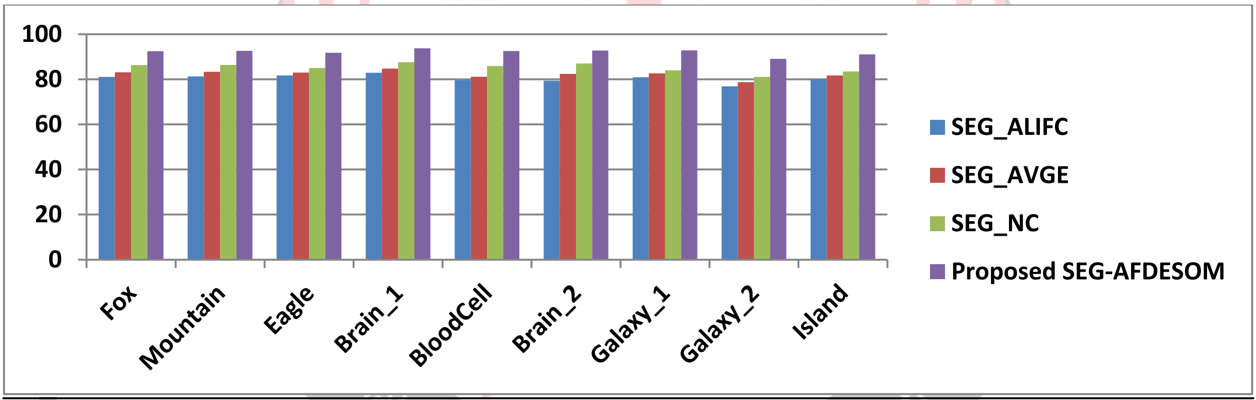

Fig. 5. Segmentation Accuracy Analysis Chart.

In the table2 and Fig.5 describe the Segmentation Accuracy analysis results of the proposed (SEG_ADFESOM) method and it reveals that the proposed method gets higher segmentation accuracy than the existing methods. In the Segmentation Accuracy analysis (SA) analysis SEG_NC is the second best method. The least best method is SEG-ALIFC. The higher SA analysis value is 92.56 in TCIA database.

Table 3. Segmentation Time Taken analysis

Database Name	**Image name**	**STT (in Sec)**			
		SEG_ALIFC	**SEG_AVGE**	**SEG_NC**	**Proposed (SEG_ADFESOM)**
DB_BSD Natural Database	Fox	27.58	28.81	27.49	**25.2**
	Mountain	27.56	28.54	27.73	**25.7**
	Eagle	26.91	28.37	27.54	**25.32**
DB_TCIA Medical	Brain_1	28.77	29.15	28.03	**26.37**

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Database	BloodCell	28.46	29.32	28.47	**26.49**
	Brain_2	28.13	28.87	28.15	**26.87**
DB_NIVL Satellite Database	Galaxy_1	28.79	29.10	27.94	**26.77**
	Galaxy_2	28.47	29.54	28.13	**26.03**
	Island	27.82	29.14	27.88	**26.41**

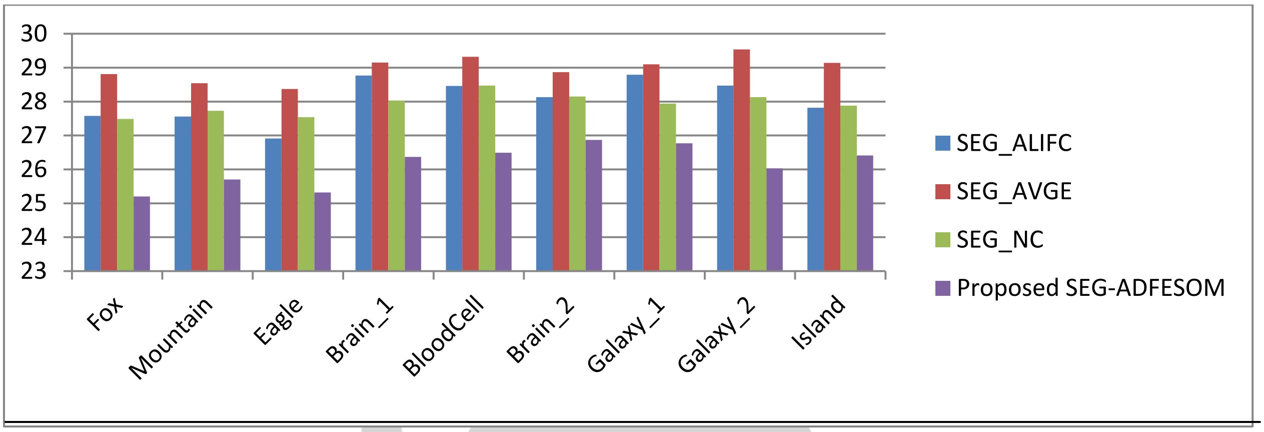

Fig. 6. Segmentation Time Taken (STT) analysis.

In the table3 and Fig.6 explains the Segmentation Time Taken (STT) analysis results of the proposed (SEG_ADFESOM) method and it reveals that the proposed method gets lower time taken than the existing methods. This method got the time is 25.2 in BSD database. The Second method SEG_NC got the time is 27.49. To compare second best method SEG_NC with proposed method the difference is 2.29.

IV. CONCLUSION

The proposed method SEG_ADFESOM is the composition of the four steps such as AWSFD noise reduction, DATBO image preprocessing, FOWLICM image clustering and Energetic SOM. The SEG_ADFESOM method is well suitable for the three types of images Natural, Medical and Satellite. The existing SOM based classification is energized via DWT transform, DCT transform and the neighbor intensity energy based similarity measure to produce an energetic segmented image. The Proposed SEG_ADFESOM is analyzed based on the Standard Analytical Measures and the evaluation process proves the energetic performance of SEG_ADFESOM than the existing versions when considering with MSE, PSNR, Accuracy, Fscore and Run-time. In the proposed SEG-ADFESOM, the PSNR gets highest value is 55.23. The difference of the second best (SEG_NC) method is 3.22. Among the three types of images the Medical images are closely united towards the proposed method's performance due to the higher degree of background-and-foreground differentiation and less noisy environment. The Overall benefits conclude that the proposed SEG_ADFESOM is the superior method of image segmentation than existing method. This method can be used as a image processing tool for green researchers because image segmentation is one of the chief preprocessing task of image processing. The future enhancement of this research can be travelled with new break through namely convolution neural network to get more accuracy. This work can be end up with future target as object.

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