International Journal of Scientific Research in Computer Science, Engineering and Information Technology
 | Volume 2 | Issue 5 | ISSN : 2456-3307

Performance Analysis of proposed Hybrid FCM Algorithms with Standard FCM for Image Segmentation

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ABSTRACT

Segmentation is defined as an image that entails the division or separation of the image into regions of equal attribute. Clustering is one of the methods used for segmentation. Numerous algorithms using different approaches have been proposed for image segmentation. Clustering is an interesting approach for finding similarities in data and putting similar data into groups. Previous records indicate that clustering is a robust tool for acquiring classifications of image pixels. In this paper, the performance evaluation of the proposed Hybrid Fuzzy C-Means Cluster Center Estimation (HFCMCCE) , Enhanced Hybrid Fuzzy C-Means Cluster Center Estimation(EHFCMCCE) and Coherence Particle Swarm Optimization Algorithm with Specified Scrutiny of Fuzzy C-Means (CPSO-SSFCM) with standard FCM, is done based on the number of iterations taken to converge for clustering, Full Reference pixel based image quality measures PSNR,MSE, classification parameters such as Sensitivity, Specificity Accuracy, Extra Fraction(EF) and Similarity Index(SI).

Keywords : Segmentation, Clustering, FCM, PSNR, MSE,SI,EF

I. INTRODUCTION

Image Analysis is extracting meaningful information from an image. Segmentation is an image analysis technique, in which different regions of an image are segregated based upon the pixel intensities available within the image [1]. Clustering methods are unsupervised segmentation methods where their no a priori knowledge is assumed to be available that partition an image into clusters of pixels with similar intensities. The unsupervised clustering can be a very effective technique to pinpoint natural groupings in data from a large data set, thereby letting concise representation of relationships embedded in the data.

There is a large literature on the image segmentation and clustering algorithms have been developed in the past few decades, with application in many areas like Medical Application, Traffic Monitoring and in Remote Sensing.

II. RELATED WORKS

A large section of researchers applied different segmentation strategies like thresholding strategy, region based methodologies, edge detection approach, clustering approaches, artificial neural network, Fuzzy procedure, watershed algorithms and others for the segmentation of various images in an attempt to achieve better results.

N. H. Harun et. al. [2] proposed 3 No's of clustering algorithms such as k-means, fuzzy c-means and moving k-means algorithms have been applied on the saturation component image. Then the median filter and seeded region growing area extraction algorithms have been applied. The comparison process is carried of the three clustering algorithms in order to evaluate the performance of each clustering algorithm on segmenting the blast area and moving k-means clustering algorithm has successfully produced the fully segmented blast region in Acute Leukemia image.

Putzu L et al.,[3] proposed methodology which allows the analysis of blood cells automatically subjected to image processing techniques, and it evolves as a medical tool to overcome the limitations exist with manual observation. This process could also be utilized for counting, as it exhibits excellent performance and paves way for early diagnostic suspicion, which can be later substantiated by a haematologist through specialised techniques.

Ronghua Shang et al., [4] proposed a clone kernel spatial FCM (CKS_FCM), which enhances segmentation performance through the generation of initial cluster centers, and by combining spatial information into the objective function of FCM and utilized a non-Euclidean distance based on a kernels metric, in place of the Euclidean distance traditionally used in FCM.

The prime objective of this paper is to perform the analysis of the various proposed segmentation algorithms with the standard FCM.

CLUSTERING TECHNIQUES

The purpose of Image Segmentation is to partition on image into meaningful regions with respect to a particular application. It can be performed effectively by clustering image pixels. Cluster analysis allows the partitioning of data into meaningful subgroups and it can be applied for image segmentation or classification purposes. FCM algorithm has greater data handling capacity and has better operability upon diversified data range. On the other hand, the convergence rate gets affected if the number of clusters and iterations are subsequently increased. Diminishing the number of iterations and clusters to obtain faster convergence rate has an adverse effect upon the segmentation accuracy. To overcome these hindrances, a novel segmentation algorithms are proposed. In this paper the standard Fuzzy C-Means is compared with various proposed Hybrid Fuzzy C-Means segmentation algorithms, HFCMCCE [5], EHFCMCCE [6] and CPSO-SSFCM [7].

A. STANDARD FUZZY C-MEANS ALGORITHM

Fuzzy C-Means was initially proposed by Bezdek et al., It is the widely used tool for image processing in clustering objects in an image. FCM facilitates the pixels to secure a place with various cluster along with alterable degrees of participation.Owing to this extra adaptability, FCM is also termed as Soft clustering strategy. But in hard clustering, the data gets portioned into a specified number of mutually exclusive subsets. Fuzzy clustering is a simple methodology when compared to the hard clustering and it carries out the non-unique partitioning of the data in a collection of clusters.

The Standard Fuzzy C-Means Algorithm is as follows:

Step1: Randomly initializing the cluster centers, termination criteria α, Maximum no of iterations X.

Step 2: Creating a distance matrix from a point $\boldsymbol{x_j}$ to each of the cluster centers using the following equation.

$$\boldsymbol{d_{ij}} = \left\|\boldsymbol{c_i} - \boldsymbol{x_j}\right\| \quad (1)$$

Step 3: Repeat the following steps until reach the total number of iterations.

Step 4: Compute the Membership matrix.

$$\boldsymbol{u_{ij}} = \frac{1}{\sum_{k=1}^{c}\left[\frac{d_{ij}}{d_{kj}}\right]^{2/(m-1)}} \quad (2)$$

Step 5: Generating new cluster centers.

$$\boldsymbol{c_i} = \frac{\sum_{j=1}^{n} u_{ij}{}^{m} x_j}{\sum_{j=1}^{n} u_{ij}{}^{m}} \quad (3)$$

Step 6: Compute the objective function.

$$\boldsymbol{J} = \sum_{j=1}^{N}\sum_{i=1}^{c}(\mu_{ij})^{m} d_{ij}{}^{2} \quad (4)$$

Step 7: Update cluster heads.

Step 8: If abs value of distance metric of J is < α Stop execution.

Step 9: Otherwise update objective function values and Go to Step 3.

B. HYBRID FUZZY C-MEANS CLUSTER CENTER ESTIMATION ALGORITHM (HFCMCCE)

Presently, utilizing the FCM calculation the image divided into a predetermined number of clusters. The following stride is to improve the image by evacuating the commotion by utilizing middle channel. The Proposed Algorithm HFCMCCE is given underneath:

Input: Gray Scale Image

Step 1: Input the dark scale image to the framework

Step 2: Partial Contrast Stretching to alter the force level of the dark scale image.

Step 3: Initialize cluster i.e. k= number of clusters

Step 4: The thickness measure esteem for the each pixel in the image is assessed by the condition.

$$D_i = \sum_{j=1}^{n} exp\left[-\frac{\left\|X_i - x_j\right\|^2}{(r_a/2)^2}\right]$$

Step 5: Select the pixel with the most astounding thickness measure as the main cluster focus and its relating thickness measure esteem as the greatest thickness measure.

Step 6: The thickness measure for every pixel worth is reconsidered by utilizing the condition

$$D_i = D_i - D_{c1} exp\left[-\frac{\|X_i - x_j\|^2}{(r_b/2)^2}\right]$$

Step 7: After the thickness measure for every pixel worth is overhauled, the following cluster focus with the most noteworthy thickness measure is chosen as a second cluster focus.
Step 8: This procedure is rehashed until a k number of cluster focuses are created.
Step 9: Initialize k cluster focuses in the FCM with cluster focus created in the progression 8.
Step 10: Calculate the Euclidean separation between each pixel of the dark scale image and cluster focus by utilizing the equation

$$d_{ij} = \left|\left|\mathbf{c}i - \mathbf{x}j\right|\right|$$

Step 11: Create participation grid by taking the fragmentary separations from the point to the cluster focus by utilizing the equation

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left[\frac{d_{ij}}{d_{kj}}\right]^{2/(m-1)}}..$$

Step 12: Generate another Fuzzy cluster focus with the condition

$$c_i = \frac{\sum_{j=1}^{n} {u_{ij}}^m x_j}{\sum_{j=1}^{n} {u_{ij}}^m}$$

Step 13: Compute the cost capacity as indicated by Equation $J(U, c_{1,\dots} c_{c})=\sum_{i=1}^{c} J_i=\sum_{i=1}^{c}\sum_{j}^{n} {u_{ij}}^m {d_{ij}}^2$ Stop if it is possible that it is beneath specific resistance esteem.
Step 14: Compute another U participation grid by Equation

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left[\frac{d_{ij}}{d_{kj}}\right]^{2/(m-1)}}$$

Go to Step 12.
Step 15: Transform the resultant cluster into image.

Output: The resultant image of leukemia influenced cells.

C. ENHANCED HYBRID FUZZY C-MEANS CLUSTER CENTER ESTIMATION ALGORITHM (EHFCMCCE)

The proposed methodology EHFCMCCE is used to further improvise the image by evacuating the commotion by involving middle channel. The Proposed Algorithm is defined as below:

A Proposed EHFCMCCE Algorithm

Step 1. Input the HFCMCCE Segmented Image.

Step 2. Applying Histogram Equalization to enhance the dark White Blood Cell (WBC) image.

Step 3. Performing Morphological operations on the histogram equalized image such as Erosion followed by Dilation and Close followed by Open resulting in a nuclei part.

Step 4. Feature extraction is carried out on the resultant nuclei part of the blood cell image.

Step 5. Image classification using SVM classifier is applied to classify the image.

Input: HFCMCCE Segmented WBC Image **Output**: A Leukemia affected Nuclei part

D. COHERENCE PARTICLE SWARM OPTIMIZATION WITH SPECIFIED SCRUTINY OF FUZZY C-MEANS (CPSO-SSFCM) ALGORITHM

The Novel coherence particle swarm optimization algorithm is integrated to the clustering algorithm in order to select the effective cluster heads. The Proposed Algorithm CPSO-SSFCM is given as follows:

Segmentation Phase

Input: Normal and Leukemia Infected Blood Microscopic Images

1. Initialize cluster numbers, Let C=**4,** Initialize the population size.
2. Initialize random cluster centre value.
3. Initialize α, initialize maximum no of iterations X.
   X=10, α=0.000001
4. Inner product norm metric is chosen (such as distance metric)
5. Initialize membership matrix using equation 2.
6. Calculate new cluster centre using equation 3.
7. Do update membership matrix and the objective function (J) using equations 2 and 4 respectively.
8. If abs value of distance metric of J is < α Stop execution
9. Otherwise update objective function values Go to Step 10.
10. Compute velocity and position using equation 5 and 6 respectively to calculate P_{Best} (Personal best).
11. If position > P_{Best} then Best position is P_{Best}.
12. If P_{Best} < G_{Best} (Global Best) then P_{Best} is the G_{Best}.
13. Update cluster head with the G_{Best}.
14. If max number of iterations not arrived go to Step 6.

Output: Segmented White Blood Cell (WBC) Image

Feature Extraction Phase

Input: Segmented White Blood Cell (WBC) Image of CPSO-SSFCM Segmentation Phase

1. Let N is the no of input images.
2. Using Canny Edge Detection extract the Nucleus (N_{ext}). and Cytoplasm ($C_{ext\,(i)}$) of the Clustered Image Cl_i.
3. Compute Region properties of Rp (N_{ext} (i)) and Rp ($C_{ext\,(i)}$).
4. Stop the execution.

Output: Extracted Nucleus and Cytoplasm of Segmented White Blood Cell (WBC) Image

III. COMPARISON PARAMETERS

3.1 PEAK SIGNAL TO NOISE RATIO (PSNR)

PSNR is the traditional measure commonly used to measures the ratio between the maximum possible power of an image and a power of corrupting noise. The PSNR is provided in decibel units (dB), it is defined as in Equation 1[8].

$$PSNR = 10\ LOG_{10}\left(\frac{(L-1)^2}{MSE}\right) \quad (1)$$

where L is the largest possible value of the signal (typically 255), Higher PSNR means more noise removed [].

3.2 MEAN SQUARE ERROR (MSE)

MSE is the cumulative squared error value between the input image A(i, j) and the segmented image B(i, j) is given in equation 2 [9].

$$MSE = \frac{1}{MN}\sum_{I=0}^{M-1}\sum_{J=0}^{N-1}[A(I,J) - B(I,J)]^2 \quad (2)$$

'm' and 'n' denote the number of rows and columns present in an input image. MSE value of the resulting segmented image should be as low as possible.

3.3 SENSITIVITY

Sensitivity is the measure of how reliable a system is at making positive identifications and it is defined as:

$$Sensitivity = \frac{TP}{TP+FN} \quad (3)$$

where TP is the true positive value.

3.4 SPECIFICITY

Specificity is a measure of how well a system can make a negative identification and it is defined as:

$$Specificity = \frac{TN}{TN+FP} \quad (4)$$

Where TN is the true negative value and FP is the false positive value.

3.5 ACCURACY

Accuracy is also called as segmentation accuracy, is an evaluation parameter used to assess the efficacy of the segmentation algorithm. The segmentation accuracy is described as the ratio of number of pixels segmented or processed by the algorithm to the total number of pixels actually present in the input image.

3.6 EXTRA FRACTION(EF)

Extra Fraction is used to measure the extent of false positive existing in the results of segmentation. The algorithm which is capable of producing lower EF value offers better segmentation results. EF is described as:

$$EF = \frac{FP}{TP+FN} \quad (5)$$

where FP - False Positive, TP-True Positive and FN-False Negative.

3.7 ELAPSED TIME

The elapsed time is the time required for the accomplishment of segmentation process is denoted in terms of seconds.

3.8 SIMILARITY INDEX(SI)

Similarity Index describes the similar or identical values between the input image and the segmented output image. It relates to the similarity found between the input image and the final segmented image. It can be calculated using formula:[9]

$$SI = \frac{2\times TP}{2\times TP+FP+FN} \quad (6)$$

IV. PERFORMANCE ANALYSIS OF PROPOSED ALGORITHMS HFCMCCE,EHFCMCCE and CPSO-SSFCM with STANDARD FCM

The performance of the various proposed segmentation algorithms is evaluated based on the measures such as number of iterations, sensitivity, specificity, accuracy, Extra Fraction, Similarity Index, and full reference pixel based measures namely, PSNR and MSE.The algorithms are applied on the blood microscopic image dataset [10] and also on standard Mat lab peppers image. The Figure1 illustrates the block diagram of the performance analysis process.

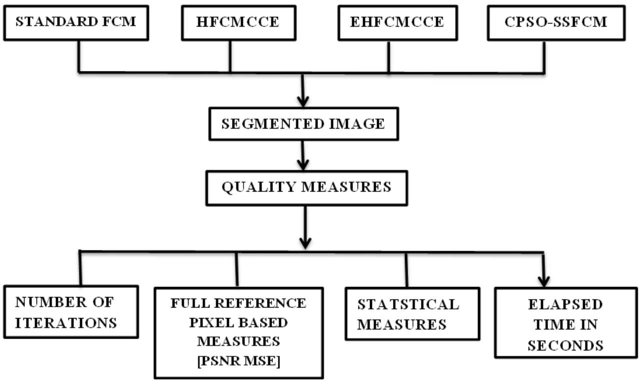

Figure 1. Block Diagram of the performance analysis Process

The Figures 2,3 and 4 shows the segmentation process of the proposed algorithms.

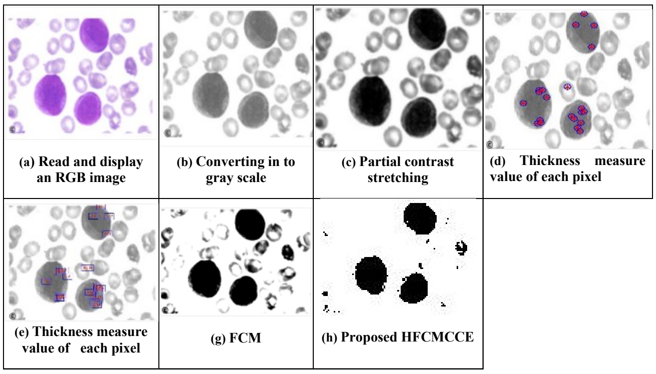

Figure 2. Segmentation result of HFCMCCEand standard FCM for leukemia infected blood cell image

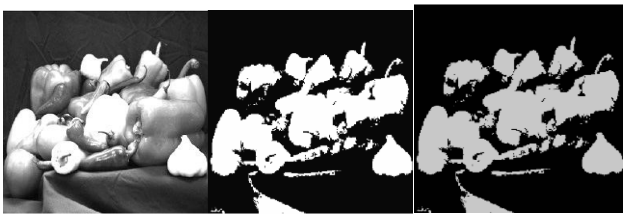

Figure 3. Segmentation of peppers image by standard FCM

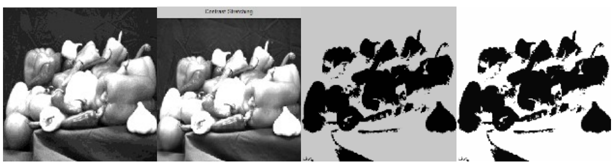

Figure 4. Segmentation of peppers image by HFCMCCE

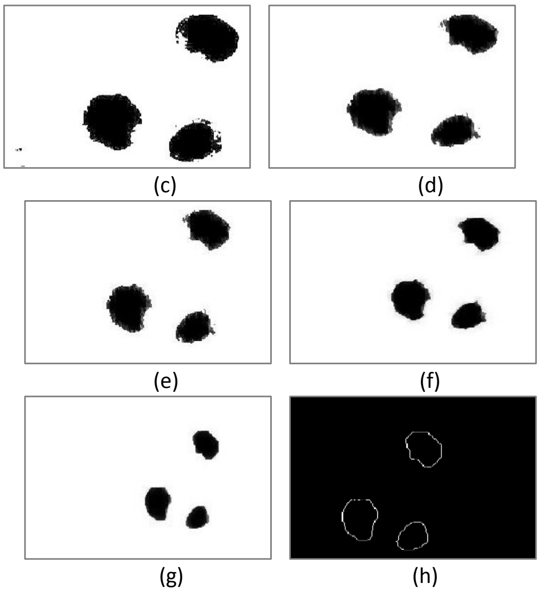

Figure 4. Extraction of Nucleus from segmented leukemia infected Blood cell image by EHFCMCCE

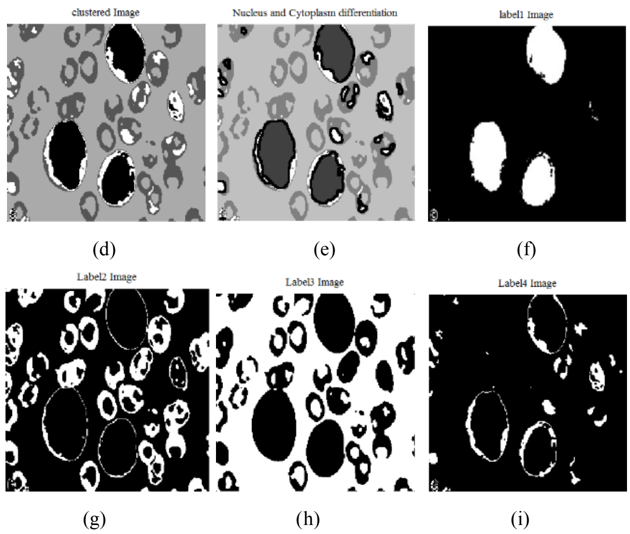

Figure 5. Segmentation results of CPSO-SSFCM for leukemia infected blood cell image

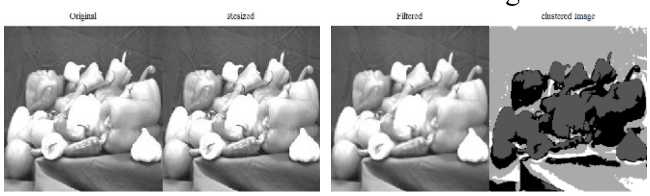

Figure 6. Segmentation of peppers image by CPSO-SSFCM

The Tables I,II,III,IV,V and VI helps us to determine the cluster heads and the total number of iterations generated by the standard FCM and proposed algorithms in segmenting the blood microscopic image and pepper image. The obtained result indicates that the proposed algorithms are having the fast convergence of cluster heads and a less number of iterations. The graphical representation of the total number of iterations is depicted in the figure 7.

The results depicted for the full reference pixel based measures PSNR and MSE are given in the table VII and in the figure 8, it is showing again that the proposed algorithms are producing the high PSNR and low MSE which in turn indicates the reconstruction of images is improved by applying the proposed algorithms than the standard FCM.

The elapsed time for the image segmentation is calculated by applying the standard FCM and proposed algorithms on blood microscopic images as well as on mat lab peppers image. For cboth the images, proposed algorithms are carrying out the segmentation in a reduced elapsed time than the standard FCM which is exhibited in the tables IX, X and in the figures 11 and 12.

The Figure 9 and Table VIII are showing the performance analysis of parameters such as sensitivity, specificity, accuracy, EF, SI compared for the EHFCMCCE and CPSO-SSFCM algorithms. Here the applying of CPSO-SSFCM produces good results by having the resultant values of 100% sensitivity, 92% accuracy, 0.99 SI value which is close to 1 and low EF. It shows that performance by CPSO-SSFCM surpass the EHFCMCCE.

TABLE I. Cluster Heads by Standard FCM for Leukemia Image

No of iterations	Cluster Head 1 (C1)	Cluster Head 2 (C2)
1	86.6089855866177	232.572337600067
2	100.079767521873	240.175384183937
3	107.324665180242	243.640468043003
4	111.1464707169	245.202443612435
5	113.102428876511	245.924700815753
6	114.085268665011	246.266893763386
7	114.574246067812	246.431790539909
8	114.816266523678	246.512061978362
9	114.935741503688	246.551355939943
10	114.994643749536	246.57064672978
11	115.023664160115	246.580131198653
12	115.037957547368	246.584797742757
13	115.044996331156	246.587094611552

TABLE II. Cluster Heads by HFCMCCE for Leukemia Image

No of iterations	Cluster Head 1 (C1)	Cluster Head 2 (C2)
1	109.740429606694	245.664013484523
2	119.172144514945	250.641678717897
3	122.039830881548	251.255063283792
4	122.833608694578	251.387531182428
5	123.052690858085	251.421976911013
6	123.113244359844	251.431354097741
7	123.129991188936	251.433936964193
8	123.134623591867	251.434650627969

TABLE III Cluster Heads by CPSO-SSFCM for Leukemia Image

No. of Iterations	Cluster Head 1 (C1)	Cluster Head 2 (C2)	Cluster Head 3 (C3)	Cluster Head 4 (C4)
1	109	57	237	95
2	125.3361	164.3961	241.3810	156.9236
3	119.5303	180.2600	248.1154	168.4684
4	- 1.7879e+03	- 2.8735e+03	- 3.7745e+03	- 2.5686e+03

TABLE IV. Cluster Heads by Standard FCM for peppers Image

No of Iterations	Cluster Head 1 (C1)	Cluster Head (C2)
1	55.2628584358533	217.610606412288
2	57.6335490728318	220.098893581724
3	58.2904865947913	221.511651498317
4	58.5523687843714	222.137443848914
5	58.6638963977682	222.405108030104
6	58.7115916688018	222.518982993066
7	58.731938436305	222.567397735448
8	58.7406031065328	222.587981430016
9	58.7442897652545	222.596733033372

TABLE V. Cluster Heads by HFCMCCE for pepper Image

No of iterations	Cluster Head 1 (C1)	Cluster Head 2 (C2)
1	54.9851	216.5827
2	57.4798	219.6754
3	58.2195	221.3327
4	58.5212	222.0615
5	58.6505	222.3729
6	58.7295	222.5616
7	58.7396	222.5855

TABLE VI Cluster Heads generated by CPSO-SSFCM for pepper image

No. of Iterations	Cluster Head 1 (C1)	Cluster Head 2 (C2)	Cluster Head 3 (C3)	Cluster Head 3 (C4)
1	147	225	223	74
2	144.0661	234.3888	227.5579	85.5026
3	-591.7549	-972.5340	-891.1454	-356.2713

Table VII. Number of Iterations in Image segmentation

ANALYSIS OF TOTAL ITERATIONS IN SEGMENTING LEUKEMIA,NORMAL BLOOD CELL IMAGE AND PEPPERS IMAGE BY STANDARD FCM , HFCMCCE and CPSO-SSFCM

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	LEUKEMIA IMAGE	NORMAL BLOOD CELL IMAGE	MAT LAB PEPPERS IMAGE
STANDARD FCM	13	8.00	9.00
HFCMCCE	8	7.00	9.00
CPSO-SSFCM	4	3.00	4.00

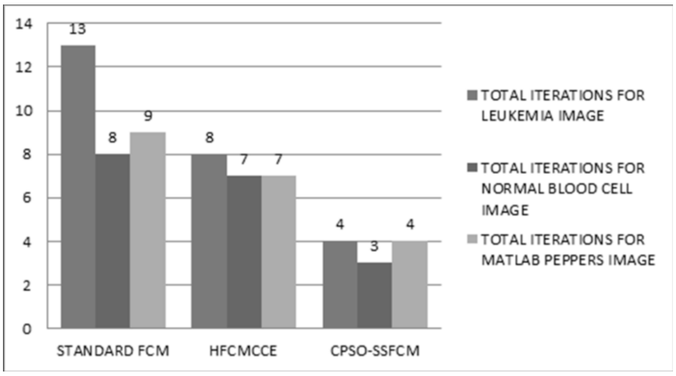

Figure 7. Performance EvaluationMat Lab Peppers Image segmentation

TABLE VIII. Performance Analysis on Full Reference and Pixel difference based Measure [Ideal values: PSNR- High, MSE-Low]

PERFORMANCE ANALYSIS OF STANDARD FCM, HFCMCCE,EHFCMCCE and CPSO-SSFCM BASED on PSNR AND MSE

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	PSNR(dB)	MSE
STANDARD FCM	26.4200	29.78
HFCMCCE	34.0800	20.73
EHFCMCCE	34.4400	18.17
CPSO-SSFCM	36.2900	15.25

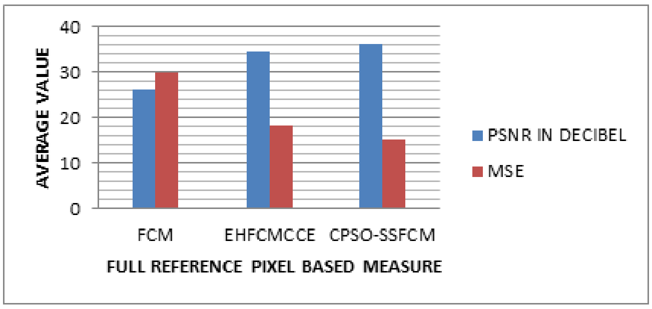

Figure 8. Performance Analysis of Full Reference and Pixel difference based Measure

TABLE VIII. Performance Analysis of EHFCMCCE and CPSO-SSFCM

PERFORMANCE ANALYSIS OF EHFCMCCE(HFCMCCE) and CPSO-SSFCM FOR CLASSIFICATION

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	EHFCMCCE	CPSO-SSFCM
SENSITIVITY	81.2500	100.00
SPECIFICITY	83.2700	83.33
ACCURACY	89.7900	92.85
EXTRA FRACTION(EF)	0.0526	0.02
SIMILARITY INDEX(SI)	0.8732	0.99

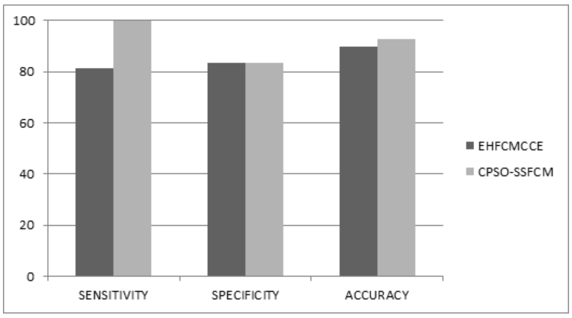

Figure 9. Evaluation of EHFCMCCE and CPSO-SSFCM on stastical mesures

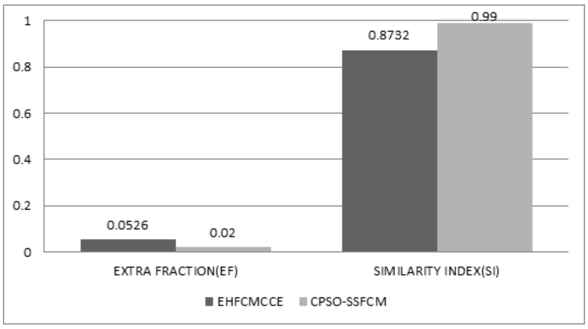

Figure 10. Performance Evaluation on Extra Fraction and Similarity Index

Table IX. Performance Analysis based on Elapsed Time Segmentation of Blood Cell Image

PEROFRMANCE ANALYSIS OF ELAPSED TIME IN SEGMENTING BLOOD MICROSCOPIC IMAGE BY STANDARD FCM , HFCMCCE and CPSO-SSFCM

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	ELAPSED TIME(SECS)
STANDARD FCM	4.1495
HFCMCCE	3.5428
CPSO-SSFCM	1.5835

Table X. Performance Analysis based on Elapsed Time Segmentation of Mat lab peppers Image

PEROFRMANCE ANALYSIS OF ELAPSED TIME IN SEGMENTING MATLAB PEPPERS IMAGE BY STANDARD FCM , HFCMCCE and CPSO-SSFCM

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	ELAPSED TIME(SECS)
STANDARD FCM	2.9374
HFCMCCE	2.0154
CPSO-SSFCM	0.7677

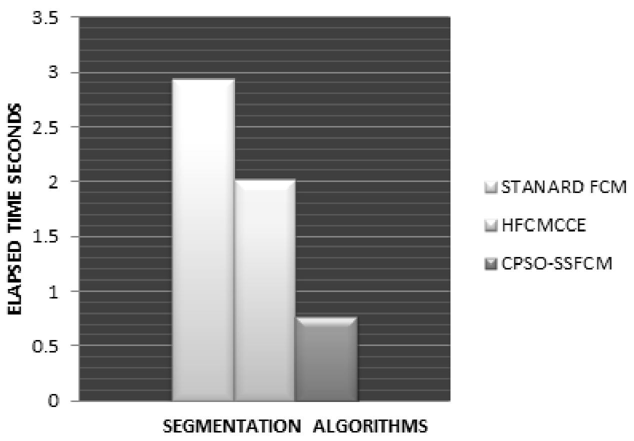

Figure 11. Performance Analysis based on Elapsed Time of for Mat lab Pepper Image Segmentation

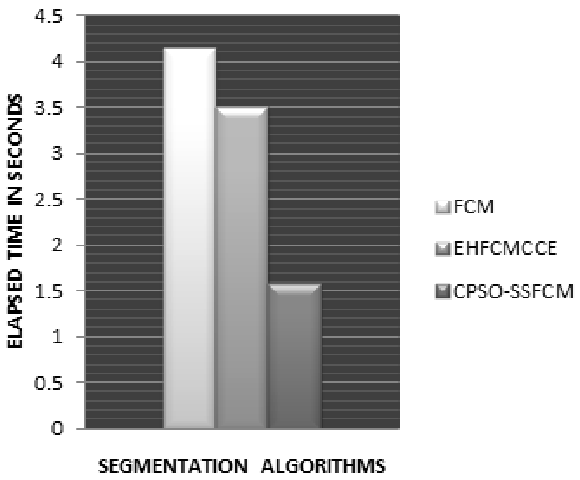

Figure 12. Performance Analysis based on Elapsed Time for Blood Microscopic Image Segmentation

V. CONCLUSION

The results demonstrate that the segmentation by hybrid algorithm excels the performance of standard FCM in the process of segmenting blood cell and mat lab images. So it could be concluded that the proposed algorithms can be utilized for medical image segmentation as well for the other matlab images. In future, the performance analysis for the proposed structure is to be exercised for additional parameters such as texture parameters etc.

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