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Image Segmentation Applying Adaptive Kernel Possibilistic C-Means with Level Set Method - A Cluster Center Initialization Approach Grounded on Cuckoo Based Search

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Abstract: In most of the vision related computer science problems, image segmentation is a crucial task. Usually, fuzzy iterative clustering algorithms are applied. In any case, the vast majority of these segmentation algorithms introduce a few disadvantages: they are tedious, and touchy to instatement and noise. Keeping in mind the end goal to defeat these issues, the methodology implemented in this paper is a novel segmentation of images. The technique is adapted to Adaptive Kernel Possibilistic C-Means (AKPCM) with Cuckoo Search Optimization (CSO) and dismissal of anomalies joined with level set method is produced. In KPCM algorithm, random selection of the initial values of cluster centers is done, but in our proposed method the existing KPCM algorithm is modified by considering the initialization of the cluster center, partition of the fuzzy matrix and the spatial information of the pixel. The cluster centers are picked ideally with the assistance of CSO algorithm. To set the underlying level set counter in the level set segmentation, the subsequent fuzzy clustering information is utilized. The algorithms were experimented over diverse sorts of images and the fragmented results show relatively good results when compared with native methods. A comparison is also carried out to demonstrate the same. Performance evaluation is conducted and a graph representing the comparative study is also depicted. The work is mostly carried out on medical images such as liver, brain etc, and it can be extended to any field of interest with a diverse set of correlations taken into consideration.

Keywords: Image Segmentation, Kernel Possibilistic C-Means, Cuckoo Search Optimization, Level Set Method, Cluster Center Initialization

1. Introduction

Image segmentation is a technique which partitions an image into uniform contextual and non - textual areas based on some closeness computation [1]. This procedure has an arrangement of using up resources, that include PC vision, examination of image, therapeutic restorative taking care of, remote detecting and organization of geographical facts or data [2]. Image segmentation fairly relies upon the key properties of an image - power values and similarity standard [3]. Image segmentation expects an imperative part in both image and video based example acknowledgment structures. In any case, it is still a testing issue for images are routinely limited by complex noise and intensity inhomogeneity [4].

The segmentation of a portion of the restorative images is a troublesome undertaking due to its minimal size, low difference, and clear brokenness of the edges [5]. In this association, assorted qualities of segmentation methodologies have been tried in the writing, including Edge Detection [6], Watershed Transformation [7], Soft Computing and Clustering strategies**.** Computing techniques that use Genetic algorithms [8, 9] and Fuzzy Logic systems [10, 11, 12]. For image segmentation are usually treated to be simple and less practical.

In this proposed work, we exhibit a novel segmentation algorithm taking into account Adaptive Kernel Possibilistic C-Means (AKPCM) and Cuckoo Search Optimization (CSO) algorithm. Regularly, in KPCM algorithm group focuses are picked haphazardly, however in our proposed strategy change the current KPCM algorithm by considering the cluster center initialization, fuzzy partition matrix, and pixel spatial data. The organizational structure adapted in the proposed paper is as follows. Section 2 lists information about some the latest research work carried out in image segmentation. Our proposed approach is described in section 3. The outcomes and their dialog alongside association is discussed in section 4. The conclusion of the paper is summarized in section 5.

2. **Related Work**

Gong, M et al. [13], applying a tradeoff weighted fuzzy factor and a kernel metric proposed an enhanced fuzzy C-means (FCM) algorithm for image segmentation.HotshotArabé S et al. [14] composed a vitality utilitarian in view of the fuzzy c-means a target capacity which joined the bias field that represented the intensity inhomogeneity of this present reality image.

Chunming Li et al. [19] proposed a variational level set framework for segmentation and bias correction of images with intensity inhomogeneities. Accuracy, efficiency, and robustness were found in the proposed method.

Gómez D et al. [15] presented the idea of Fuzzy Image Segmentation. They proposed an algorithm considering the current relations between the fuzzy boundary set issue and the (crisp) progressive image segmentation issue. They drafted their work on fuzzy boundaries fabrication.

Zhao, X et al. [16] proposed a fuzzy clustering algorithm taking into account Mahalanobis separation. It characterizes the disparity measure by Mahalanobis separation rather than Euclidean separation, in light of the fact that the Euclidean separation was touchy to noise and uniqueness of clusters.

Feng Zhao et al, in their paper proposed an Optimal-selection-based suppressed fuzzy c-means clustering algorithm with self-tuning non local spatial information for image segmentation [18]. However the α parameter is not referred. The clusters are set manually which is not ideal. A spatial model can be induced alongside with the self tuning non local spatial information.

Hari Jyothula et al[21], in the paper proposed a Level set model implementing Local Binary Fitting and Particle Swarm Optimization. Numerical tests on the images show that the proposed calculation is stable, and achieves huge enhancements. However, the work is carried out on remedial data. Hari Jyothula et al[22], in the paper Local Chan-Vese along with some enhancement methods for minimization of vitality capacities to defeat power inhomogeneity and commotion have been incorporated. By consolidating this implanted approach, the images with force inhomogeneity have been effectively divided.

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K.S.Tan et al. [2] proposed an approach which applies the histogram thresholding technique to obtain all possible uniform regions in the color image. They used the Fuzzy C-means (FCM) algorithm is to improve the compactness of the clusters that form the uniform regions.
An iterative watershed algorithm and artificial neural network mechanism is proposed in the paper by Hassan et al.[20]. Multiple slices can be considered instead of a single slice.
L. Wang et al. [4] proposed a novel segmentation algorithm via a local correntropy-based K-means (LCK) clustering. As a result of the correntropy criterion, the clustering algorithm can decrease the weights of the samples that are away from their clusters. The LCK based clustering algorithm can be robust to the outliers. The proposed LCK clustering algorithm is incorporated into the region-based level set segmentation framework. The iteratively re-weighted algorithm is used to solve the LCK based level set segmentation method.

3. Adaptive Kernel Possibilistic C-Means (Akpcm) Based Image Segmentation

Segmentation of images demonstrates an essential part in an assorted qualities of use, for example, object acknowledgment, robot vision and medical imaging. A few strategies have been presented for image segmentation which we as of now gave in section 1 and 2. That said a strategy has been used for moderately for ordinary structures, for complex kinds of information clustering methods are utilized.

3.1 Kernel Possibilistic C-Means (KPCM)

Typically, FCM strategy continues by rehashing the vital circumstances until an answer is come to. Every data point joined with participation esteem for every class after FCM clustering. The FCM target is to characterize the cluster centers and to produce the class association matrix. Let I = {x_n} an image, n = {1, 2, 3 . . .} where x_n are the pixels of *I* and *i* is the cumulative amount of pixels. The FCM strategy reduces the following objective function

$$J_{FCM} = \sum_{n=1}^{v}\sum_{m=1}^{i}\mu_{nm}^{k} d^2\left(x_m, C_n\right) \tag{1}$$

Where μ_{nm} = membership function matrix,

d = Euclidean separation matric between x_j and the cluster center C_n ,

k = level of fuzziness (k>1).

The imperative part of the FCM is the membership function μ_{nm} where the membership degrees and the cluster centers are linked as

$$\mu_{nm} = \frac{1}{\sum_{j=1}^{v}\left(d_{nm}/d_{jm}\right)^{2/(k-1)}} \tag{2}$$

$$C_n = \frac{\sum_{n=1}^{i}\mu_{nm}^{k}x_m}{\sum_{m=1}^{i}\mu_{nm}^{k}} \tag{3}$$

In clustering issues, the choice of metric is imperative. Because of the effortlessness and in addition generally utilized utilization of Euclidean distance metric, the hypothesis that the clusters have super round shapes and also the information are uncorrelated which is wrong in segmentation of image; subsequently, the Mahalanobis separation is more proper. Regularly, a few issues like sturdiness against noise, outliers, and arbitrarily molded clusters limits are there consequently to beat these issues, as of late proposed the subsequent objective function

$$J_{PCM} = \sum_{n=1}^{v}\sum_{m=1}^{i}\mu_{nm}^{k} d^{2}\left(x_m, C_n\right) + \sum_{n=1}^{v}\eta_n \sum_{m=1}^{i}\left(1-\mu_{nm}\right)^{k} \tag{4}$$

Where *d*= Mahalanobis distance.

$$d^{2}\left(x_m, C_n\right) = \left(x_m - C_n\right)^{T} S_n \left(x_m - C_n\right) \tag{5}$$

$$S_n = \left|\Sigma_n\right|^{\frac{1}{p}} \sum_{1}^{-1} \tag{6}$$

Where p=1, the issue measurement and η_n are sure numbers. In equation (4), the principal term bolsters for a smallest space between data points and models, μ_{nm} ought to be immense as likely. The η_n are chosen as

$$\eta_n = M \frac{\sum_{m=1}^{i}\mu_{nm}^{k}\left\|x_m - C_n\right\|^{2}}{\sum_{m=1}^{i}\mu_{nm}^{k}} \tag{7}$$

M is preferred to be 1, and the PCM memberships are updated as

$$\mu_{nm} = \frac{1}{1+\left(\left(\left\|x_m - C_i\right\|^{2}\right)/\left(\eta_n\right)\right)^{(1)/(k-1)}} \tag{8}$$

The KPCM objective function and the membership updating functions given by

$$J_{KPCM}\left(U, C\right) = \sum_{n=1}^{v}\sum_{m=1}^{i}\mu_{nm}^{k}\left\|\Phi\left(x_m\right) - \Phi\left(C_n\right)\right\|^{2} + \sum_{n=1}^{v}\eta_n \sum_{m=1}^{i}\left(1-\mu_{nm}\right)^{m} \tag{9}$$

$$\mu_{nm} = \frac{1}{1+\left(\frac{2\left(1-M\left(x_m . C_n\right)\right)}{\eta_n}\right)^{(1)/(k-1)}} \tag{10}$$

Here we utilized the Gaussian function as kernel function, and η_n are assessed utilizing

$$\eta_n = M \frac{\sum_{m=1}^{i}\mu_{nm}^{k} 2\left(1-M\left(x_m, C_n\right)\right)}{\sum_{m=1}^{i}\mu_{nm}^{k}} \tag{11}$$

Typically, M is selected as 1.

The strategies shown above suffers with step initialization, spatial data, outlier dismissal and space metric issues in keeping in view of end goal to overcome that we propose Adaptive Kernel Possibilistic C-Means algorithm with Cluster Center Initialization utilizing CSO algorithm.

3.2 Proposed Adaptive Kernel Possibilistic C-Means (AKPCM)

For the most part, in KPCM algorithm, the underlying estimation of cluster centers are picked randomly, yet in our proposed strategy we adjust the current KPCM algorithm by considering the cluster focus initialization, fuzzy partition matrix, and pixel spatial data. The strides required in the segmentation technique are given as below

- Cluster Center Initialization utilizing CSO algorithm
- Design of membership function for AKPCM algorithm by considering outlier rejection.
- Spatial data is composed using square window around the present pixel
- Finalization of Segmentation by Level Set Method

Cluster Center Initialization using CSO algorithm

In the initialization step, a CSO is utilized to cluster focus initialization and the membership function. This algorithm includes a nets or eggs populace. For ease, the resulting representations are used; where every egg in a net means an answer and a Cuckoo egg means another one. On the off chance the egg of the Cuckoo is placed extremely parallel to the host's egg. In that case, the currently placed Cuckoo's egg will not be uncovered, thus the wellness must be related to the arrangement divergence. The main goal is to utilize fresh and conceivably upgraded arrangements of Cuckoos to trade terrible arrangement in the homes.

In CSO, the resulting three romanticized standards are used

- The eggs the cuckoo lays, one at a time are automatically dumped into a subjectively picked nest.
- The finest nests with high caliber of eggs are continued to the following steps
- The accessible number of host homes is steady, and the egg of the Cuckoo is uncovered by the host fowl with a probability of pop p_a in the middle of 0 and 1. The later notion can be assessed by the part pop p_a of the n homes which is traded by new ones.

At first, one of the subjectively picked nests (barring the finest one) is exchanged by another arrangement made by irregular stroll with Lévy flight across the currently best nest, consideringthe quality. While delivering new arrangements, x_i^{t+1} for the i^{th} Cuckoo, a Lévy flight is accomplished using the following equation

$$x_i^{(t+1)} = x_i^{(t)} + \alpha.S \tag{12}$$

Where α > 0 is the progression size factor and must be chosen considering the size of the issue and is set to solidarity in the CSO. The length of irregular stroll with Lévy flights is taken with parameter S. It is indicated by the Mantegna's algorithm as

$$S = \frac{u}{|v|^{1/\beta}} \tag{13}$$

Where β is a parameter which is a constant measured to be *1.5*, *u* and *v* are drained from normal distribution as

$$u \sim N\left(0, \sigma_u^2\right), \qquad v \sim N\left(0, \sigma_v^2\right) \tag{14}$$

Where

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}} \right\} \qquad \sigma_v = 1 \tag{15}$$

The parameter p_a is deliberated as the likelihood of a solution element to be exposed. Hence, a likelihood matrix is created as:

$$P_{ij} = \begin{cases} 1 & if\ rand < pa \\ 0 & if\ rand \geq pa \end{cases} \tag{16}$$

Where 'rand' is an irregular number between 0 to 1

Step 1: Initialization: (v: number of class, k>1: level of fuzziness, CSO parameters) furthermore instate populace of n host homes $x_i(i = 1,2,...,n)$

Step 2: Calculating the degrees of membership $\left(u^{(0)}{}_{nm}\right)$ given in equation (10) by means of the Euclidean separation.

Step 3: Acquire a cuckoo haphazardly by Levy flights

Step 4: Calculate the Mahalanobis distance $U^{(p-1)}$ in equation (5) and (6)

Step 5: Calculate $U^{(p)}$, using equation (10)

Step 6: Calculate the wellness capacity Fi on premise of Mahalanobis separation.

Step 7: Select a nest among n (say j) arbitrarily

Step 8: Calculate the wellness capacity Fj on premise of Mahalanobis separation.

Step 9: If $F_i \geq F_j$ Supplant j by fresh arrangement

End

Step 10: Unrestraint a part (p_a) of most exceedingly terrible nest and assemble new ones at new areas by means of duty flights.

Step 11: Preserve the best arrangements (or nests with quality arrangements)

Step 12: Grade the arrangements and trace the existing finest.

Step 13: Terminate if most extreme condition fulfilled

Interim and $P_{ij}$is deciding probability for j[th] factor of i[th] home. The pseudo code for instatement using CSO isdepicted in the following algorithm.

Design of membership function for AKPCM algorithm

By and large, the KPCM uses a metric which is extremely delicate to anomalies. The KPCM membership function is modified by considering the outliers rejection then the equation (9) gets to be

$$J_{AKPCM} = \sum_{n=1}^{v}\sum_{m=1}^{i}\mu_{nm}^{k}\alpha^{\|\Phi(x_m)-\Phi(C_n)\|^2} + \sum_{n=1}^{v}\eta_n\sum_{m=1}^{i}(1-\mu_{nm})^k \qquad (17)$$

The model of AKPCM is given by

$$\min J_{AKPCM} = \min\left(\sum_{n=1}^{v}\sum_{m=1}^{i}\mu_{nm}^{m}\alpha^{\|\Phi(x_k)-\Phi(C_n)\|^2} + \sum_{n=1}^{v}\eta_n\sum_{m=1}^{i}(1-\mu_{nm})^k\right) \qquad (18)$$

The KPCM algorithm's membership function is altered by interchanging the original distance term given in equation (10).

$$\mu_{nm} = \frac{1}{1+\left(\dfrac{\alpha^{\|\Phi(x_m)-\Phi(C_n)\|^2}}{\eta_n}\right)^{1/k-1}} \qquad (19)$$

$$\eta_n = M\frac{\sum_{m=1}^{i}\mu_{nm}^{k}\alpha\|\Phi(x_m)-\Phi(C_n)\|^2}{\sum_{m=1}^{i}\mu_{nm}^{k}} \qquad (20)$$

The exponent role α is to minimize the partial dissemination of points between two neighboring clusters rather than expanding it to all clusters. α is expressed as

$$\alpha = \frac{Intensity\ range\ in\ the\ image+1}{Maximum\ Intensity\ range+1}+1 \qquad (21)$$

For an 8 bit grey scale image, equation (21) is:

$$\alpha = \frac{(X_{\max}-X_{\min})+1}{256}+1 \qquad (22)$$

Where $X_{\max}$ is the most extreme intensity of the image and $X_{\min}$ is the least intensity in the image. α Range between 1 and 2. In the scenario that the image has an extraordinary power reach, α is nearer to 2, the incomplete circulation of the pixels between two neighboring clusters is diminished. Far-fetched, if the result of the image has a slight intensity reach, α is approximately close to 1 and the halfway circulation of pixels is just between neighboring clusters.

Spatial Information

All the adjacent pixels in an image are extremely correlated. To prove this, we define a spatial function which is as follows:

$$h_{nm} = \sum_{j\in NB(x_m)}\mu_{nj} \qquad (23)$$

Where $NB(x_m)$ is a squared window centered on the pixel x_j .We utilize a 3 x 3 window and h_{nm} is the likelihood that the pixel x_m belongs to n^{th} cluster. Thus the membership function in equation (19) becomes

$$\mu^*_{nm} = \frac{\mu_{nm}{}^p h_{nm}{}^q}{\sum_{j=1}^{v} \mu_{jm}{}^p h_{jm}{}^q} \quad (24)$$

Where *p* and *q* are parameters utilized to control the weight of each function.

Finalization of Segmentation by Level Set Method

Image segmentation by method for active counters is a surely understood methodology. As an option of a parametric representation of the active counters, level set strategy embed them into a period dependent halfway differential equation function $\psi(t, x, y)$. At that point it is liable to estimate the development of the active counters in a roundabout way by taking after the level set $\Gamma(t)$. So as to naturally introduce the level set introductory form, the subsequent clustering is accomplished by utilizing AKPCM.

$$\begin{cases} \psi(t,x,y) < 0 & (x,y) \ is \ inside \ \Gamma(t) \\ \psi(t,x,y) = 0 & (x,y) \ is \ at \ \Gamma(t) \\ \psi(t,x,y) > 0 & (x,y) \ is \ inside \ \Gamma(t) \end{cases} \quad (25)$$

Γ may be consist of a solitary or a zero is contours series which can be effortlessly determined by checking the level set function values ψ, which adjusts to the deviations of the implied interface Γ. The evolution termination is defined by

$$\begin{cases} \dfrac{\partial \psi}{\partial t} + F|\nabla \psi| = 0 \\ \psi(0,x,y) = \psi_0(x,y) \end{cases} \quad (26)$$

Where $|\nabla \psi|$ = normal direction,

$\psi_0(x, y)$ = initial contour and

F = comprehensive intensities.

By an edge indication function *g, t*he evolving intensity F needs to be normalized to stop the level set progression near the optimal solution.

$$g = \frac{1}{1 + |\nabla(G_\sigma * I)|^2} \quad (27)$$

Where $G_\sigma * I$ is the complexity among the Gaussian kernel G_σ and the image *I*. ∇ signifies the gradient operator. Level set segmentation is expressed as:

$$\frac{\partial \psi}{\partial t} = g|\nabla \psi| \left(div\left(\frac{\nabla \psi}{|\nabla \psi|} \right) + v \right) \quad (28)$$

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Where $div\left(\frac{\nabla\psi}{|\nabla\psi|}\right)$ estimates the mean curvature κ and v is a customable balloon intensity. A level set was given by

$$\frac{\partial\psi}{\partial t} = \mu\varsigma(\psi) + \xi(g,\psi) \quad (29)$$

Where $\zeta(\psi)$ the penalty is motion of ψ and $\xi(g,\psi)$ is an image gradient data

$$\xi(g,\psi) = \lambda\delta(\psi) + div\left(g\frac{\nabla\psi}{\|\nabla\psi\|}\right) + vg\delta(\psi) \quad (30)$$

Where $\delta(\psi)$ is the Dirac function. v, μ And λ are parameters to regulate the level set function. The flowchart of the proposed method is shown in figure 1.

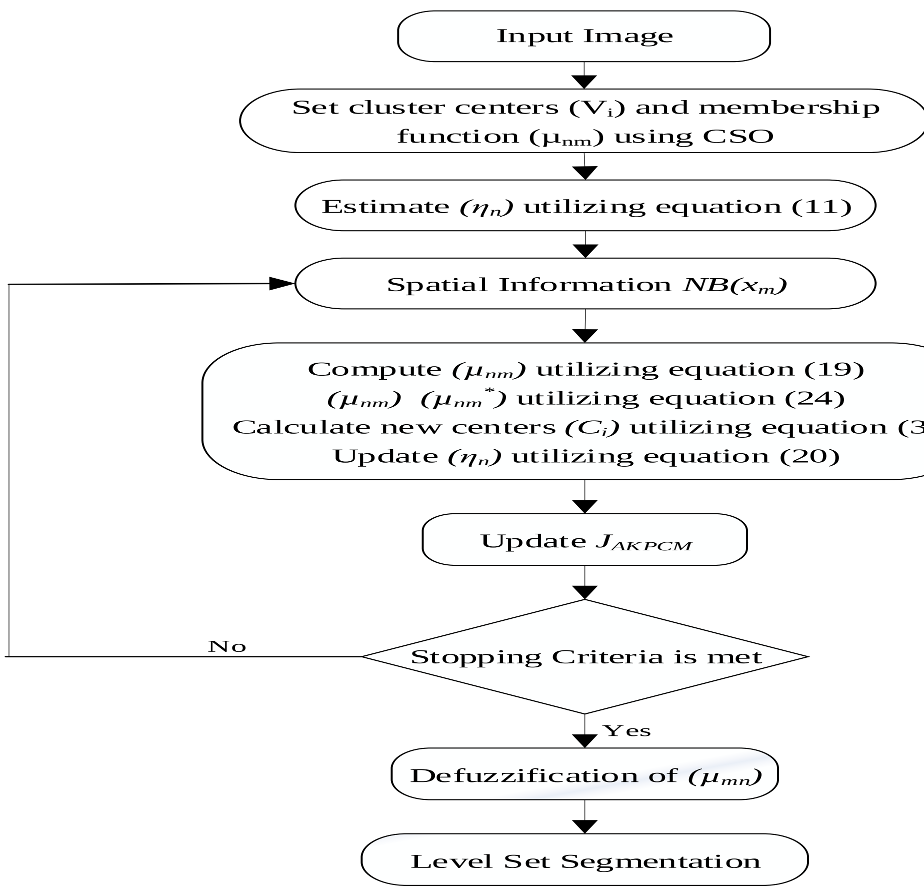

Figure 1: Flowchart of the Proposed Method

4. Experimental Results& Discussions

In this proposed system we exhibit a productive technique for image segmentation taking into account AKPCM and CSO algorithm. In this proposed system we have utilized diverse sorts of images and the

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fragmented results are given underneath. In this proposed technique we made a correlation with standard KPCM algorithm and reproduced results are introduced.

4.1 Medical Images

The content of a healthy brain can be categorized into three tissues. They are the white matter (WM), the cerebrospinal fluid (CSF) and the gray matter (GM). The algorithmic parameters, in particular the estimations of m, the quantity of clusters c and the vectors structure communicating to the image pixels are characterized. The segmented result acquired by the proposed technique and the standard KPCM algorithm is depicted in figure 2

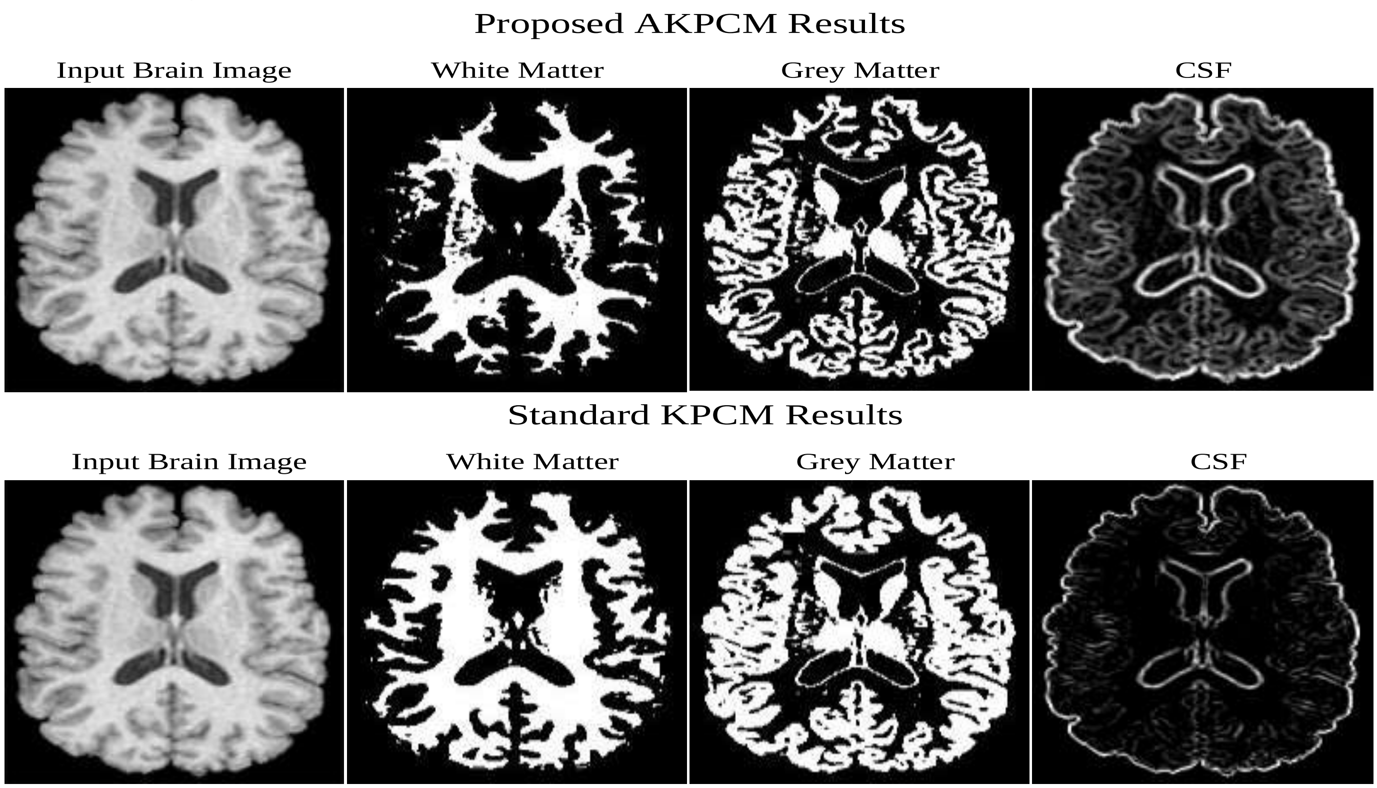

Figure 2: Results of MRI Brain Image

From the images, we can't affirm that the proposed technique has accomplished better results we have to investigate in light of certain execution measure which is appeared in coming areas. Additionally, we have considered another kind of Medical Image that is liver image with two dangerous locales. The segmented results acquired by the proposed technique and the standard KPCM algorithm are appeared in figure 3.

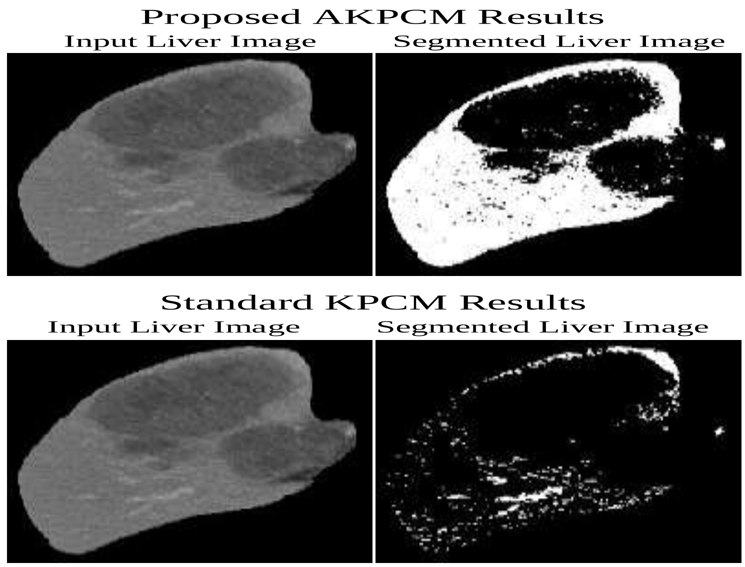

Figure 3: Results of Liver Image

On account of liver image likewise we have gotten better results, this we can see from the figure 3 there is an expansive distinction between the proposed strategy and standard KPCM technique here for liver image additionally we displayed the execution measure investigation. Next with a specific end goal to demonstrate that our proposed technique not just appropriate for medicinal image it is likewise reasonable for other common images which we have appeared in next section.

4.2 Other Images

Image segmentation not just assume a noteworthy part in medical application it likewise assumes a noteworthy part in different fields. So we composed a technique which is not just reasonable for medicinal images it likewise appropriate for other sort of images. Here we consider other image is flower the segmented image of flower is appeared in figure 4

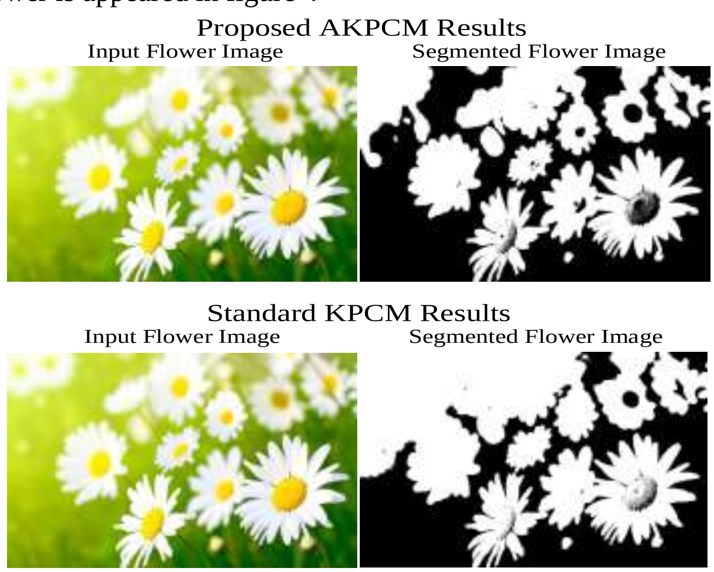

Figure 4: Segmented Flower Image

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From the above figure, (figure 4), it is evident that our proposed technique has precisely fragmented the flower though standard KPCM algorithm likewise portioned precisely in a few districts just at the upper left corner we can see that the segmentation is not clear this is a direct result of arbitrary cluster center initialization while our proposed strategy has accomplished exact segmentation on account of streamlined cluster center initialization by CSO this affirms the significance the proposed technique for the flower image additionally we have displayed execution measure in later section.

Here, in our proposed technique for completion of segmentation we have utilized level set segmentation which is the last stride in our segmentation. To assess the sustainability of fuzzy clustering for level set segmentation the experiments are carried on the past medical images and normal images. The segmented results after a few emphases for various kinds of images are appeared in figure 5-6.

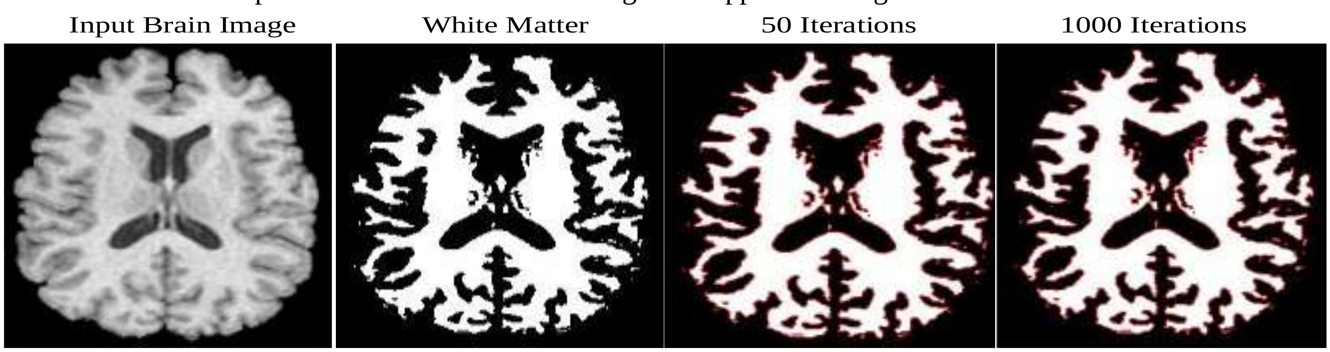

Figure 5: Level set segmentation of Brain Image

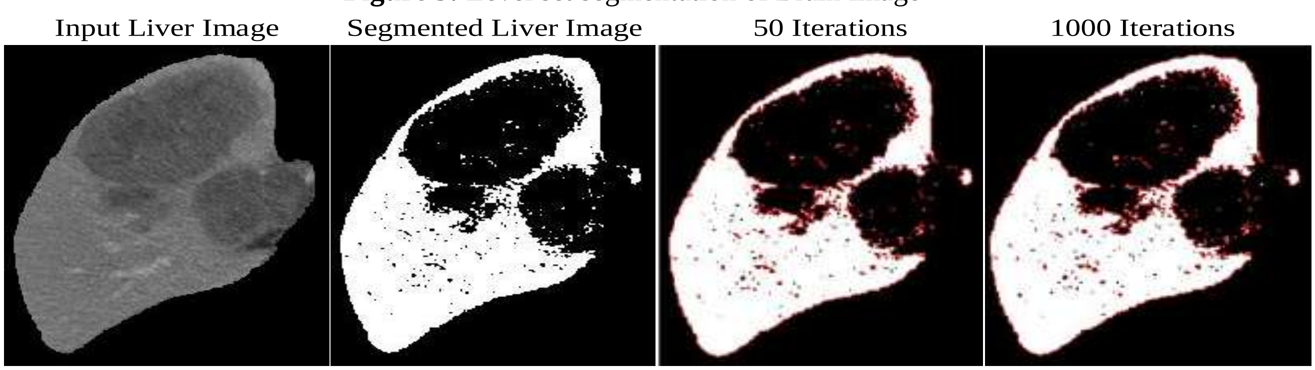

Figure 6: Level set segmentation of Liver Image

Figure 5-6 exhibits the outcomes after such a variety of emphases a superior segmentation is accomplished in view of the AKPCM and the execution measure for the distinctive images is appeared in next section.

4.3 Performance Evaluation

The following parameters are considered for performance evaluation. They are the Dice and Jaccard Index, True Positive and False Negative Fraction (TPF & FNF), False Positive and True Negative Fraction (FPF & TNF). The formula used for calculating these parameters are

$$\text{Dice Index} = \frac{2\left|R_t \cap R_g\right|}{\left|R_t\right| + \left|R_g\right|} \tag{31}$$

$$\text{Jaccard Index} = \frac{R_t \cap R_g}{R_t \cup R_g} \tag{32}$$

$$\text{TPF} = \frac{R_t \cap R_g}{R_g} \tag{33}$$

$$\text{FNF} = \frac{R_g - R_t}{R_g} \tag{34}$$

$$\text{FPF} = \frac{R_t - R_g}{R_g} \tag{35}$$

$$\text{TNF} = 1 - \frac{R_t - R_g}{R_g} \tag{36}$$

Where R_t is the resulting image and $R_g$is the ground accurate image. The performance for the three types of images for standard KPCM algorithm is shown in table 1 and for proposed AKPCM is shown in table 2 and the performance graph is shown in figure 7.

Table 1: Performance Measure for KPCM

Images	**Dice**	**Jaccard**	**TPF**	**FNF**	**FPF**	**TNF**
Brain (WM)	0.95	0.89	0.92	0.08	0.13	0.87
Brain (GM)	0.93	0.86	0.88	0.12	0.15	0.85
Brain (CSF)	0.94	0.88	0.91	0.09	0.12	0.88
Liver Image	0.96	0.88	0.93	0.07	0.12	0.88
Flower Image	0.95	0.90	0.9	0.10	0.14	0.86

Table 2: Performance Measure for AKPCM

Images	**Dice**	**Jaccard**	**TPF**	**FNF**	**FPF**	**TNF**
Brain (WM)	0.97	0.90	0.94	0.06	0.06	0.94
Brain (GM)	0.96	0.92	0.91	0.09	0.07	0.93
Brain (CSF)	0.98	0.91	0.95	0.05	0.05	0.95
Liver Image	0.97	0.93	0.95	0.05	0.03	0.97
Flower Image	0.98	0..95	0.97	0.03	0.02	0.98

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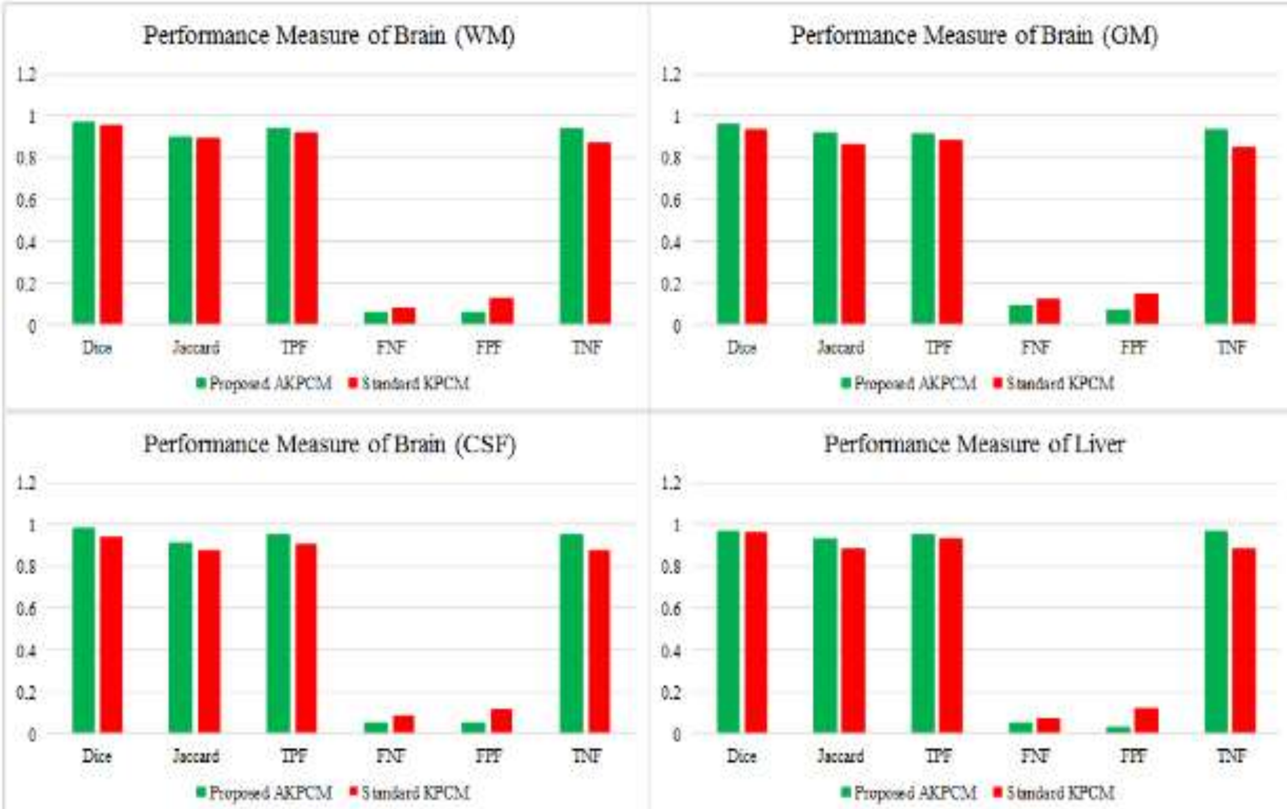

Figure 7: Performance Comparison

From figure 7, we can see that the proposed technique has achieved change in all measurements like Dice index, Jaccard index, TPF, FNF, FPF, and TNF this outcomes indicates scientifically demonstrated the viability of the proposed strategy likewise from the fragmented results images we can plainly see the significance of the cluster center initialization. Consequently from the got results we can affirm that proposed technique is the best strategy and most reasonable technique for image segmentation.

5. Conclusion

In this proposed procedure, we have presented an AKPCM. In the standard KPCM algorithm; we have blended cluster center initialization, fuzzy partition matrix, and pixel spatial data. For cluster center initialization and membership function, CSO which is better contrasted and other metaheuristic algorithms are used. The proposed AKPCM has been tried on various sorts of images like brain, liver, and other common images. For conclusion of segmentation, level set methodology has been utilized and a sensible segmentation and extraction of different regions has been accomplished. The work is mostly carried out on medical as well as common images, and can be extended to any field of interest.

References

[1] G Dong, and M Xie, “Color clustering and learning for image segmentation based on neural networks, “IEEE Transactions on Neural Networks, Vol. 16, No. 4, pp. 925–936, 2005.

[2] Tan K. S, and Isa N. A. M, “Color image segmentation using histogram thresholding–Fuzzy C-means hybrid approach”, Pattern Recognition, Vol. 44, No. 1, pp. 1-15, 2011.

[3] Muthukrishnan R, and M Radha, "Edge detection techniques for image segmentation", International Journal of Computer Science & Information Technology, Vol. 3, No. 6, 2011.

[4] Wang L, and Pan C, “Robust level set image segmentation via a local correntropy-based K-means clustering”, Pattern Recognition, Vol. 47, No. 5, pp. 1917-1925, 2014.

[5] Wang L, Chen Y, Pan X, Hong X, and Xia D, “Level set segmentation of brain magnetic resonance images based on local Gaussian distribution fitting energy”, Journal of neuroscience methods, Vol. 188, No. 2, pp. 316-325, 2010.

[6] Aquino A, Gegúndez-Arias M. E, and Marín D, “Detecting the optic disc boundary in digital fundus images using morphological, edge detection, and feature extraction techniques”, IEEE Transactions on Medical Imaging, Vol. 29, No. 11, pp. 1860-1869, 2010.

[7] Tarabalka Y, Chanussot J, and Benediktsson J. A, “Segmentation and classification of hyperspectral images using watershed transformation”, Pattern Recognition, Vol. 43, No. 7, pp. 2367-2379, 2010.

[8] Abbasgholipour M, Omid M, Keyhani A, and Mohtasebi S. S, “Color image segmentation with genetic algorithm in a raisin sorting system based on machine vision in factor conditions”, Expert Systems with Applications, Vol. 38, No. 4, pp. 3671-3678, 2011.

[9] Senthilnath J, Kalro N P, and Benediktsson J. A, “Accurate point matching based on multi-objective genetic algorithm for multi-sensor satellite imagery”, Applied Mathematics and Computation, Vol. 236, pp. 546-564, 2014.

[10] Balla-Arabe, Souleymane, Bin Wang, and XinboGao, "Level set region based image segmentation using lattice Boltzmann method", In Proceedings of IEEE International Conference on Computational Intelligence and Security (CIS), pp. 1159-1163, 2011.

[11] Jaffar M, Arfan, AyyazHussain, and Anwar MajidMirza, "Fuzzy entropy based optimization of clusters for the segmentation of lungs in CT scanned images", Knowledge and Information Systems, Vol. 24, No. 1, pp. 91-111, 2010.

[12] Niknam T, and Amiri B, “An efficient hybrid approach based on PSO, ACO and k-means for cluster analysis”, Applied Soft Computing, Vol. 10, No. 1, pp. 183-197, 2010.

[13] Gong M, Liang Y, Shi J, Ma W, and Ma J, “Fuzzy c-means clustering with local information and kernel metric for image segmentation”, IEEE Transactions on Image Processing, Vol. 22, No. 2, pp. 573-584, 2013.

[14] Balla-Arabé S, Gao X, and Wang B, “A fast and robust level set method for image segmentation using fuzzy clustering and lattice Boltzmann method”, IEEE Transactions on Cybernetics, Vol. 43, No. 3, pp. 910-920, 2013.

[15] Gómez D, Yáñez J, Guada C, Rodríguez J. T, Montero J, and Zarrazola E, “Fuzzy image segmentation based upon hierarchical clustering”, Knowledge-Based Systems, Vol. 87, pp. 26-37, 2015.

[16] Zhao, Xuemei Yu Li, and Quanhua Zhao, "Mahalanobis distance based on fuzzy clustering algorithm for image segmentation", Digital Signal Processing, 2015.

[17] Yang, X. S., & Deb, S. (2009, December). Cuckoo search via Lévy flights. In Nature & Biologically Inspired Computing, 2009.NaBIC 2009. World Congress on (pp. 210-214). IEEE.

[18] Feng Zhao, Jiulun Fan , Hanqiang Liu, “Optimal-selection-based suppressed fuzzy c-means clustering algorithm with self-tuning non local spatial information for image segmentation” Expert Systems with Applications, 2014 journal homepage: www.elsevier.com/locate/eswa (pp. 4083 - 4093)

[19] Chunming Li, Rui Huang, Zhaohua Ding, J. Chris Gatenby, Dimitris N. Metaxas, *Member, IEEE*, and John C. Gore, “A Level Set Method for Image Segmentation in the Presence of Intensity Inhomogeneities With Application to MRI”, IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 20, NO. 7, JULY 2011 (pp 2007 – 2016)

[20] Hassan Masoumia, AlirezaBehradb, Mohammad Ali Pourminaa, AlirezaRoostaAutomatic liver segmentation in MRI images using an iterative watershedalgorithm and artificial neural network.., Biomedical Signal Processing and Control 7 (2012) (pp 429– 437)

[21] Hari Jyothula, Koteswara Rao S., ValliKumari V. Applying Level Set and Optimization Technique for image segmentation to Avoid Noise and Intensity Inhomogeneity. Journal of Social, Technological and Environmental Science •v.6, n.2, may-august. 2017 (p. 299-306)

[22] Hari Jyothula, Koteswara Rao S., ValliKumari V. Integration of Local Chan Vase along with Optimization techniques for Segmentation. 978-1-5386-1887-5/17/$31.00 ©2017 IEEE conference. International conference on Energy, Communication, Data Analytics and Soft Computing (ICECDS - 2017)