Optimized Segmentation of Tissues and Tumors in Medical Images using AFMKM Clustering via Level Set Formulation

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Abstract

One of the significant difficulties in image analysis is image segmentation. For different applications numerous segmentation algorithms have been presented and created. Now and again inadmissible outcomes have been experienced, for number of existing segmentation algorithms. Here we propose a novel clustering technique called Optimized Adaptive fuzzy moving k-means (AFMKM) clustering algorithm using level set formulation for medical image segmentation such as tumors and tissues in MRI brain and CT scan Images. The Proposed technique is describing in two steps for accurate image segmentation. The first step is the pre-processing of our approach; firstly we are combining the particle swarm optimization- (PSO) algorithm and Adaptive fuzzy moving k-means- (AFMKM) clustering algorithm called an Optimized AFMKM clustering algorithm. In this step, automatic chosen of an optimal cluster centers with the help of PSO algorithm instead of random choosing of cluster centers. Second step of our approach, the AFMKM clustering is implemented to level set method for accurate and superior detection of edges and boundaries of the tissues and tumors in medical images. The proposed method got the satisfactory and superior results over the conventional level set methods.

Keywords: Medical Images, Brain as well as Bone Tissue Sarcoma, Particle swarm optimization (PSO), Adaptive Fuzzy Moving K-Means-AFMKM and Level set model.

INTRODUCTION

Digital image processing is a zone portrayed by the requirement for broad exploratory work to build up the reason-ability of proposed answers for a given issue. An imperative trademark basic the outline of image processing frameworks is the significant level of testing as well as experimentation that ordinarily is required before touching base at an adequate arrangement. This trademark suggests that the capacity to define approaches &quickly model competitor arrangements by and large assumes a noteworthy part in diminishing the cost and time required to touch base at a practical framework usage.

The image might be communicated as a 2D capacity f(x, y), at which x and y represents spatial directions, and the ‘f ’ adequacy at any combine of directions (x, y) is called as intensity (or) gray level of an image. At whatever time x, y as well as the sufficiency estimations of ‘ f ’ meant for the most part limited discrete amounts, we call the image as a digital image. The field of Digital image processing alludes to handle the digital image by the methods of digital-computer. Digital image is prepared out of a predetermined number of components, every one of which has a particular region and esteem. The components were pronounced as pixels.

Vision is the best exceptional of a sensor, so it isn't amazing that image plays a most vital part in human observation. Not with standing, not under any condition like individuals, who are confined to the visual band of the EM range imaging machines’ cover about the entire EM range, reaching out from gamma to radio waves. They can work in like manner on images made by sources that individuals are not accustomed with band together with image. There is no wide attestation among the creators regarding wherever image handling stops as well as other related regions, for example, image analysis& computer vision begin. Once in a while a qualification is made by characterizing image handling as a train in which both the information and yield at a procedure are images. This is constraining and to some degree fake limit. The zone of image analysis is in the middle of image preparing as well as computer vision.
Be that as it may, one helpful worldview is to think about three kinds of computerized procedures: low-level, mid-level, and abnormal state forms. A Low-level process comprises of crude operations, for example, image handling to diminish commotion, differentiate upgrade and additionally image enhancing. Mid-level technique on images includes assignments, for an example, like segmentation, portrayal of that question decrease them to a frame reasonable for computer proceeding as well as order of individual objects. The mid-level method is represented by means of a way that its sources of information for the most component are images conversely its yields are qualities detached from those images. At long last a more elevated amount system incorporates "Comprehending" a gathering of perceived objects, as in image analysis and at the furthest finale of a continuum playing out the psychological capacities ordinarily connected with a human vision.

Segmentation using fuzzy techniques, especially FCM is widely used in medical images since it is capable of collecting more information about the original image compared with other clustering approaches. The well-known process or technique fashionable in fuzzy segmentation method for noise or sound free images is a Standard unsupervised FCM clustering algorithm. Different clusters with membership of varying degrees are belonged to pixels which are allowed by this FCM. As medical images contains unusual noise which is done by patient movements, performance of operator, instruments in hospital and the surrounding disturbances. The standard FCM cannot remove these noises because it is suitable only for images which are noise free. In order to remove these additional noise neighborhood information is also considered, which is impossible in standard FCM. For this reason FCM algorithm becomes problematic intended for medical image segmentation [1-5].

Therefore, even by added noise our proposed method is more reliable with the consideration of constraints such as member in it, typicality and neighborhood information of both local and nonlocal by combining adaptive FCM and K-Means clustering algorithms to create a new clustering approach called ‘Adaptive fuzzy moving k-means’- (AFMKM) clustering algorithm. In the images and segments there will be some specific noise and that can be specifically controlled by this method. This is possible with PSO algorithm is combined with this clustering algorithm. This is the major advantage of our clustering algorithm; even in the proposed techniques is suffered with edge and boundary leakage problems. To overcome these leakages, we are implementing proposed clustering algorithm to level set method.

Here the arranged types of Level set image segmentation techniques can comprehensively of two ways. They were i) region based segmentation and ii) edge based. 'Geodesic Active Contour- (GAC) is most chosen technique in an edge based active contour technique which develops the gradient of an image for the purpose of acquiring the edge stopping function- (ESF) to localize a contour about boundaries of the preferred object.

Majority of an active contours utilize the balloon forces’ to evolve a contour which is very complex or unpredictable to design. Here Balloon force sign decides the evolving contour’ positive for contracting as well as negative for an extension. For an expansive balloon forces the contour evolves faster conversely it might go through feeble edges and the contour might not be permitted in the event that it is little. Edge based technique’s neglects to distinguish inside and outside boundaries of the object if the initial contour characterized is a long way from preferred object as per these Active Contour Models- (ACM's) are inclined to local minimum.

Most of the dis-advantages which were occurred in edge based ACMs can be overcome by a model known as Region based ACMs. These are very less sensitive towards noise as well as gives a very worthy performance of an images with fragile or without edges since they use statistical data within the contour or outside the contour. Although, an initial contour is well-defined far away from an object, it has ability to identify interior as well as exterior boundaries’ of a preferred object. The most prominent active contours without edges is executed by Chan and Vese et.al which exhibits the level set model that limits the Mumford-Shah function introduced in.

A C-V prototype had a possessions of global segmentation which segments entire an objects within the image irrespective of an initial contour. Though the GAC show distinguishes an interior boundaries if the contour’ is characterized inside an object as well as identifies an exterior boundaries if it is outside, so that it can be treated as a local segmentation model. So here in, this paper we introduce a new method to segment medical images is Adaptive fuzzy moving k-means - (AFMKM) clustering algorithm’ this cannot be segmented efficiently with GAC as well as C-V prototypes independently. Here the suggested ACM is established on the advantages of GAC as well as C-V prototypes or models, which utilizes a particle swarm optimization-(PSO) as an additional constraints. At last, we got a precise as well as accurate segmentation results were possible with PSO which is combined with suggested clustering using level set formulation [6-10].

This paper will be systematized as follows. Section II will give information regarding the Particle swarm optimization-(PSO); Section III is all about 'Adaptive fuzzy moving k-means’- (AFMKM) clustering algorithm. Section IV provides the detailed information about level set formulation; Section V gives experimental results are given.
PARTICLE SWARM OPTIMIZATION - (PSO) ALGORITHM

Kennedy and in addition Eberhart (1995) [11-13] stayed enlivened to have an improvement in look system of PSO by the scavenging conduct of groups of fowls and schools of fish. Each and every particle has its own position and additionally velocity, at which the qualities speaks to the factors of choice in the present emphasis and additionally the development vector for the following cycle, separately. The velocity and additionally the position of each and every particle as needs be varieties to the information which is partaken in the middle of each particle in the present cycle. Each particle can record the individual single and additionally revive through cycles or by following a procedure. The worldwide best commonality was characterized by looking at the individual best recognition of all particles. The pursuit procedure of PSO includes perceiving the new velocity keeping in mind the end goal to have figuring of a position which is another one at the following procedure as per the velocity which is unique of an each and every particle (vi), the individual best commonality of each and every particle (x_p(i)), and the worldwide best nature of each particles(x_g) which is appeared in Fig.1. PSO could get a surmised ideal arrangement by rehashing the grouping or process over number of development emphases.

\[
\begin{align*}
    v_{id}(t+1) & = w\ast v_{id}(t) + c_1 r_1(x_{p(id)}(t) - x_{id}(t)) + \\
    & + c_2 r_2(x_{g(id)}(t) - x_{id}(t)) \\
    x_{id}(t+1) & = x_{id}(t) + v_{id}(t+1)
\end{align*}
\]

At which \( v_{id}(t) \) indicates the value of velocity of \( d_{id} \)
Dimension of \( i_{th} \) particle in \( t_{id} \) iteration .A variable \( x_{id} \) \( x_{id}(t) \) indicates the location of \( d_{id} \) dimension if the \( i_{th} \) particle in \( t_{id} \) iteration .A variable \( w \) indicates the weight of inertia, \( c_1 \) is the self-cognition acceleration co-efficient, and \( c_2 \) is a social-cognition acceleration co-efficient.

Fig.2. which demonstrates the procedure to be looked by PSO. Principal Step is to instate particle swarm and furthermore incorporate particles velocity and also position in the space looking. Afterward, ascertain the wellness of the particle swarm so as to refresh the individual best recognition of each and every particle and in addition the worldwide best nature of each particle. The most vital preparing step is that to figure the novel velocity as well as the location of every particle in the following procedure by utilizing the conditions (1) and (2).
were produced independently. Range of uniform distributed random numbers are (0, 1). The below segment depicts quickly about these two classes' of estimations of parameter segment

BASIC CLUSTERING ALGORITHMS: A REVIEW

K-Means Clustering Algorithm:

It’s an iterative, numerical, un-supervised as well as non-deterministic in nature. The system takes a basic and simple approach to arrange a given informational index through a specific number of groups. At last, this calculation goes for limiting a target work acknowledged as squared error function given below:

\[
J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_i} (\| x_i - v_j \|)^2
\]

(3)

At which,

\[
\| x_i - v_j \| \quad \text{- is a Euclidean distance between xi and vj.}
\]

\[
c_i \quad \text{-is the number of data points in } i^{th} \text{ cluster.}
\]

\[
c \quad \text{- is the number of cluster centers.}
\]

Algorithm for K-Means:

Consider \( X = \{x_1,x_2,x_3,\ldots, x_n\} \) which is a set of data points as well as \( V = \{v_1,v_2,\ldots, v_c\} \) which is a set of centers. Haphazardly pick a ‘c’ cluster centers and process the separation between every datum point as well as cluster centers. Assign the information point to the cluster center whose partition from the gathering center is in particular the cluster center. Calculate the new group focus utilizing:

\[
\mu_j = \frac{1}{\sum_{k=1}^{c} \left( \frac{d_j}{d_k} \right)^{2/(m-1)}}
\]

(6)

Now compute fuzzy centres \( v_j \) by using:

\[
v_j = \left( \sum_{i=1}^{n} (\mu_j)^m x_i \right) / \left( \sum_{i=1}^{n} (\mu_j)^m \right), \forall j = 1,2,\ldots,c
\]

(7)

Repeat calculating the fuzzy membership and fuzzy centres till a minimum ‘J’ values which had to be obtained otherwise \( \| U(k+1) - U(k) \| < \beta \), at which ‘m’ is an fuzziness co-efficient, ‘k’ is meant for an iteration step, ‘\( \beta \)’ represents a termination criterion between \([0, 1]\), ‘U’ = ( \( \mu_j \) ) \( n \times c \)’ is a fuzzy and ‘J’ represents the objective function a matrix.

Fuzzy K-Means Clustering Algorithm:

The fuzzy k-means – (FKM) clustering algorithm, an idea of fuzzy logic is presented. The primary thought of acquainting it is with potentially enable every datum part to be doled out at the same time to more than one class by various level of participation i.e., k-clusters are assembled at the same time utilizing both enrolment capacities from FCM and centroid area utilizing K-means algorithm. An iterative procedure with broad calculations is normally required to create an arrangement of cluster representatives.

Algorithm for Fuzzy K-Means Clustering Algorithm:

Information an arrangement of beginning cluster centres \( SC_0 = \{c_j(0)\} \) and the estimation of \( \varepsilon \) (threshold esteem) and set \( p=1 \). Given the arrangement of cluster centres \( SC_p \), figure d for \( I = 1 \) to \( N \) and \( j = 1 \) to \( k \). Refresh enrolments u utilizing the accompanying condition:
\[ u_{i,j} = \left( \frac{1}{(d_{ij})^{1/m-1}} \right)^{-1} \left( \sum_{l=1}^{k} \left( \frac{1}{d_{lj}} \right)^{1/m-1} \right)^{-1} \]  \[ (8) \]

Register the inside for each cluster utilizing the condition to acquire another arrangement of group agents \( SC_p+1 \).

\[ C_j (p) = \frac{\sum_{i=1}^{N} u_{ij}^m X_i}{\sum_{i=1}^{N} u_{ij}^m} \]  \[ (9) \]

If \( ||C(p) - C(p-1)|| < \varepsilon \) aimed at \( j = 1 \) to \( k \), at that point stop, where \( \varepsilon > 0 \) is a little positive number. Generally set \( p + 1 \rightarrow p \) and back to refreshing participation function.

**Adaptive Moving K-Means Clustering Algorithm:**

The proposed adaptive moving k-means (AMKM) clustering algorithm provides a solution to this problem by assigning the members of the center with the largest fitness value if \( V_i < Cl \) to the nearest cluster depending on the minimum Euclidean distance. The way toward reassigning the individuals is not the same as the conventional MKM as the individuals from the centre with the biggest fitness esteem are traditionally allocated to the inside with the smallest fitness esteem. At that point, the places of all the current clusters are recalculated. The reassigning individuals' method will fundamentally keep away from the requirement of information to unseemly focuses or clusters.

**OPTIMIZED AFMKM CLUSTERING ALGORITHM**

**Adaptive Fuzzy Moving K-Means Clustering Algorithm:**

The suggested clustering algorithm known as 'Optimized Adaptive Fuzzy Moving K-Means Clustering Algorithm' (AFMKM) combines the concepts introduced is the previous proposed two clustering algorithms (i.e. the FMKM as well as AMKM algorithms) and Particles swarm optimization (PSO) algorithm. The Optimized AFMKM thus derived from the basic algorithms improves the properties of image segmentation by adding the definite properties such as fuzziness, adaptability, degree of membership etc, and helps in extracting the desired segmented output of the image that is taken from the real world medical images like MRI brain and CT scans Images.

**Algorithm for Adaptive Fuzzy Moving K-Means Clustering:**

**Step 1:** Optimal cluster centers are extracted from Eq.(1) and (2) with the help of particle swarm optimization algorithm and set

\[ \alpha_a = \alpha_b = \alpha_o \]  \[ (10) \]

Where \( \alpha \) is a constant which should be 0.2.

**Step 2:** Specify the membership for each data using the equation

\[ m_{ik} = \frac{1}{\sum_{j=1}^{c} \left[ \frac{d_{ik}}{d_{jk}} \right]^{2/m-1}} \]  \[ (11) \]

Where, \( d_{ik} \) be the distance between the data point and current cluster, \( d_{jk} \) be the distance between the data point and other cluster and \( m \) be the weight updating factor.

**Step 3:** Assign all data to the nearest center and calculate the center position using the equation

\[ C_j = \frac{1}{n_j} \sum_{i \in c_j} v_i \]  \[ (12) \]

Where \( c_j = i^{th} \) centre and \( v_i = i^{th} \) data.

**Step 4:** Check the fitness of each center using the equation

\[ f(C_j) = \sum_{i \in c_j} (||v_i - C_j||)^2 \]  \[ (13) \]

**Step 5:** Find Cs as well as Cl (i.e., the middle that has littlest and biggest fitness esteem.

\[ \text{IF} \quad f(C_s) < \alpha_a f(C_i), \quad \text{IF} \quad v_i < Cl \]

move the part to the closest cluster contingent upon least Euclidean separation and leave whatever remains of the individuals to Cl. Recalculate the places of Cs and Cl and Update \( \alpha_a \) as per

\[ \alpha_a = \alpha_a - \alpha_a / n_c \]

And repeat until

\[ f(C_s) \geq \alpha_a f(C_i) \]  \[ (14) \]

**Step 6:** Reassign all data to the nearest center and recalculate the center position.
Update $\alpha_a$ and $\alpha_b$ according to

$$\alpha_a = \alpha_o \quad \text{and} \quad \alpha_b = \alpha_h - \alpha_b / n_c \quad \ldots \ldots (15)$$

**Step 7:** Repeat the steps until from calculating $C_s$ and $C_l$ and updating $\alpha_a$ and $\alpha_b$ till

$$f(C_s) \geq \alpha_b f(C_l)$$

Advantages of Optimized Adaptive Fuzzy Moving K-Means Clustering Algorithm are less sensitive to noise, Dead centres, center redundancy and trapped centres at local minima can be avoided, less sensitive to initialization of clustering value, Object size and shape are maintained and preserved.

**Implementation of Optimized AFMKM Clustering to Level Set method**

The proposed algorithm optimized AFMKM clustering is implementation to level set approach for proper boundary detection of the object details. As the information determined vitality term and also relating penalty term is portrayed in above segment. The total plan about level set in this approach is communicated as [14-22].

$$F = \epsilon + \mu R_p(\phi) + V |C| + gE_{\text{shape}} \quad (16)$$

At which $\mu$, $v$, $g$ were the weighting co-efficient of relating regularized term. Supplanting $\epsilon$, $R_p(\phi)$, $|C|$ as well as $E_{\text{shape}}$, we can re-compose the level-set function as

$$F(\phi, u, b) = \frac{\sum_{i=1}^{n} \int [K(d) v'(x) - u_i b(y)]M_i(\phi(x)) + \frac{1}{2} \int [\nabla x - \hat{y}]^2 dx + v \int \phi(x) \nabla \phi(x) dx}{\int \phi(x) dx} + g \int \left[ H(\phi(x)) - H(\psi(x)) \right] dx \quad (17)$$

Keeping in mind the end goal to disentangle the articulation, we characterize

$$e_i = \int k(d) v'(x) - u_i b(y)^2 dx \quad (18)$$

Along these lines, the level set capacity can be communicated as

$$F(\phi, u, b) = \frac{\sum_{i=1}^{n} e_i M_i(\phi(x)) + \frac{v}{2} \int [\nabla x - \hat{y}]^2 dx + v \int \phi(x) \nabla \phi(x) dx}{\int \phi(x) dx} + g \int \left[ H(\phi(x)) - H(\psi(x)) \right] dx \quad (19)$$

By limiting this capacity, we can get the segmentation aftereffect of prostate MR image which is indicated by the bend of level set capacity $\phi$. The minimization of this capacity can be achieved by an iterative procedure which is limiting the capacity $F$ as for its factor's $\phi$, $u_i$ as well as $b$ respectively. The arrangement as for every factor is appeared as takes after.

For $\phi$, we must fix $u_i$, $b$, as well as utilize stand gradient descent technique to resolve the gradient flow condition.

$$\frac{\partial \phi}{\partial t} = \frac{\epsilon}{\mu}$$

As $\frac{\partial \phi}{\partial t}$ is the gateaux derivative of energy function $F$.

Through calculating this gateaux equation, we have

$$\frac{\partial \phi}{\partial t} = -\delta(\phi)(c_i - e_i) + v \delta(\phi) \frac{\nabla \phi}{\nabla \phi} + \mu \delta(d_x) \left\{ [\nabla \phi] \frac{\nabla \phi}{\nabla \phi} \right\}$$

$$+ 2g \delta(\phi) \left[ H(\phi) - H(\phi) \right]$$

At which $\nabla$ is the gradient operator, divergence operator is $\text{div} (.)$ the as well as $d_p$ is the function which is defined as

$$d_p(s) = \frac{p(s)^2}{s} \quad (22)$$

For $u_i$, by setting $\delta$, $\epsilon$, the optimal $u_i$ can be attained by calculating partial differential $\frac{\partial F}{\partial u_i}$.

$$u_i = \frac{\int \left( (K^* b) v M_i(\phi(y)) \right) dy}{\int (K^* b^2) M_i(\phi(y)) dy} \quad (23)$$

Where (*) indicates a convolutions operation.

For $b$, by fixing $\delta$, $u_i$ the optimal $b$ can be gained through calculating the partial differential

$$\frac{\partial F}{\partial b} b = \frac{(v^2 \sum_{i=1}^{n} u_i M_i(\phi(y))) \ast K}{(\sum_{i=1}^{n} u_i^2 M_i(\phi(y))) \ast K} \quad (24)$$

The streamlining of level set capacity can be communicated as the accompanying procedure:

**First step:** Instate the level set capacity $\phi(x)$

**Second step:** Modernize $\phi(x)$ by using

$$\phi_{n+1} = \phi_n + \theta \frac{\partial \phi}{\partial t}, \theta \quad \text{is step size as well as} \quad \frac{\partial \phi}{\partial t}$$

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represented in condition (21). Modernize $\mathcal{U}_t$ which is signified in condition (23). Modernize $b$ signified in condition (24). Compelling the zero level set $c$ transfer in the direction of the borderline of prostate organ.

**Third step:** Crisscross the convergence’ of an energy function $F$. The convergence’ criteria used in this methodology is 

\[
|F^{(n)} - F^{(n-1)}| \leq \eta,
\]

at which $F^{(n)}$ is the $n^{th}$ iteration consequence of $F$, as well as $\eta$ is set to 0.001.

**RESULTS AND DISCUSSIONS**

Three unique biomedical images for segmentation of bone tissues and tumors in colonoscopy images. The proposed results are analyzed and associated with the C-V active contour prototype or model as well as DRLS as shown in figure 3. The proposed segmentation results are accurate and faster based on the following parameters i.e tuning parameter, segmentation accuracy (SA), iterations, area error calculations and CPU time of biomedical images.

Our proposed level set method segmenting colonoscopy regions accurately and effectively when compared with conventional methods. The database was taken from the brain web simulated database. These images were rescaled to 256x256 for contour evolution of the both suggested and conventional methods for preprocessed images. An initial contours for the four images’ were taken as square shaped initial contour functions defined from 10 to (N-100)th pixels of a NxN size input image. The final contour evolution to the desired output had taken within a range of 50 – 120 iterations with less CPU time.

In figure 3, the segmentation results from left to right. Figure 3a represents the original biomedical images colonoscopy, cardiac vascular and knee respectively. Figures 3b, 3c and 3d were the segmentation results with the C-V model, DRLSE model, and proposed model respectively. Figure 1e is the corresponding segmented regions of proposed algorithm. The existing level set models fails to recognize the best possible edges, regions and boundaries of images for the evolution of the level set contour. Because of it is a restricted curve advancement approach with inherent limitations of edge based model and delicate to the initial location of the level curve.

The proposed final level set segmentation results cover the maximum segmented area compared with conventional models. The performance parameters of our proposed model and conventional prototypes were tabulated in table 1, table 2 and table 3. Quantitative evaluation performances of segmentation results of previous and proposed approaches are given in table 1 and 2 respectively.

A pixel based quantitative evaluation approach is used. In this evaluation approach made a comparison between the final segmented image ‘P’ and ground truth image ‘Q’. The segmentation similarity coefficient (SSC) is measured with the help of Dice as well as Jaccard co-efficient’. For the higher values of the Dice as well as Jaccard co-efficient’ gives the better performance. The Dice as well as Jaccard index can be defined as

\[
\text{Dice} = \frac{2|P \cap Q|}{|P| + |Q|}, \quad \text{Jaccard} = \frac{P \cap Q}{P \cup Q}
\]

In table 1 and 2, the proposed model is faster, accurate and superior for detection of tumors and tissues in medical images based on the dice and jaccard similarity coefficients. All the experimentation is done on MATLAB R2014a 32b in Windows 10 OS with Intel(R) dual Core(TM) 32bit processor, CPU @ 1.80 GHz, 2 GB RAM. The CPU time is recorded for all the algorithms are tabulated in table 1 and 2.

The figure 4 depicts the extraction of the segmented regions of Brain Image (example) using conventional and proposed methods. Our method segments a more regions compared to conventional technique as shown in figure 4a and 4b respectively.
Figure 3. Segmentation of proposed model as well as well-known existing models for detection of tissues and tumors in colonoscopy cancer, cardiac vascular and knee biomedical images from left to right: Column (a) is the Original test images column (b) is the Level Set evolution with ACM model [7] column (c) is the segmentation results by DRLSE model [20] column (d) and (e) are the segmentation results of our proposed level set model and its corresponding segmented regions respectively.
Table 1. Performance Analysis of well-known existing models and Proposed Level set model in terms of Dice Similarity (DS) index and Jaccard Similarity (JS) index measures.

<table>
<thead>
<tr>
<th>Images</th>
<th>Chane–Vese(C-V) model</th>
<th>DRLSE Model</th>
<th>Proposed LevelSet Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DS Index</td>
<td>JS Index</td>
<td>DS Index</td>
</tr>
<tr>
<td>Image1 (Colon Image1)</td>
<td>0.8380</td>
<td>0.7212</td>
<td>0.7039</td>
</tr>
<tr>
<td>Image2 (Colon Image2)</td>
<td>0.8715</td>
<td>0.7724</td>
<td>0.7659</td>
</tr>
<tr>
<td>Image3 (MRI brain)</td>
<td>0.8440</td>
<td>0.7301</td>
<td>0.7085</td>
</tr>
<tr>
<td>Image4 (Knee Image)</td>
<td>0.8432</td>
<td>0.7290</td>
<td>0.4994</td>
</tr>
</tbody>
</table>

Table 2. Performance Analysis of well-known existing models and Proposed Level set model in terms of iterations, CPU time(s) and Area Error measures.

<table>
<thead>
<tr>
<th>Images</th>
<th>Chane–Vese(C-V) model</th>
<th>DRLSE Model</th>
<th>Proposed LevelSet Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>iterations</td>
<td>evolution time</td>
<td>Area error</td>
</tr>
<tr>
<td>Image1</td>
<td>120</td>
<td>18.2210s</td>
<td>10610 mm²</td>
</tr>
<tr>
<td>Image2</td>
<td>80</td>
<td>20.2210s</td>
<td>7874 mm²</td>
</tr>
<tr>
<td>Image3</td>
<td>100</td>
<td>15.9481s</td>
<td>12603 mm²</td>
</tr>
<tr>
<td>Image4</td>
<td>50</td>
<td>9.93538s</td>
<td>9953 mm²</td>
</tr>
</tbody>
</table>

Table 3. Comparative analysis of existing and proposed algorithms for segmented area calculations of different images

<table>
<thead>
<tr>
<th>image</th>
<th>Accurate area</th>
<th>Conventional C-V model</th>
<th>DRLSE model</th>
<th>proposed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image1</td>
<td>38066 mm²</td>
<td>27456 mm²</td>
<td>20676 mm²</td>
<td>35511 mm²</td>
</tr>
<tr>
<td>Image2</td>
<td>34596 mm²</td>
<td>26722 mm²</td>
<td>15266 mm²</td>
<td>33455 mm²</td>
</tr>
<tr>
<td>Image3</td>
<td>46706 mm²</td>
<td>34103 mm²</td>
<td>25625 mm²</td>
<td>42407 mm²</td>
</tr>
<tr>
<td>Image4</td>
<td>36731 mm²</td>
<td>26778 mm²</td>
<td>15860 mm²</td>
<td>28805 mm²</td>
</tr>
</tbody>
</table>
CONCLUSION

A suggested Optimized ‘Adaptive Fuzzy Moving K-Means Clustering Algorithm’ - AFMKM gives better results than other basic algorithms (K-means, FCM, FKM and AMKM). The segmented parts can be seen clearly with the proposed level set method. This method is more accurate algorithm to improve the segmentation results. In our algorithm’ PSO with AFMKM is performed in the primary step for improving the clustering efficiency and information of mutually local as well as nonlocal are included into the AFMKM objective utility which is modified by distance metric. Later, in secondary step, for achieving the robust image segmentation using a level set method-(LSM). The segmentation accuracy is measured based on two similarity metrics Dice Similarity and Jaccard similarity. To demonstrate the superiority of our proposed method we compared our results Chan-vase and DRLSE level set models. Thus our proposed method can show better results than all other two methods.

REFERENCES


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