AN EVOLUTIONARY ALGORITHM BASED MULTI-LEVEL THRESHOLDING ON MEDICAL IMAGE SEGMENTATION

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ABSTRACT

Image segmentation is an important process in image processing applications. Segmentation aims to partition the pixels of the images into several class labels which enables the investigations of the objects that exist in the image. Multi-level thresholding is an easier process which aims to determine the optimal set of threshold values which is applied to effectively segment the images. Kapur’s entropy based segmentation is applied to identify the optimal threshold values. Since the computation of many thresholding values is highly complex, it can be considered as an NP hard problem and can be resolved using evolutionary algorithms. This paper presents a new evolutionary algorithm based multilevel thresholding based segmentation (EA-MLTS) technique for brain tumor diagnosis. The presented EA-MLTS technique aims to segment the brain tumor using magnetic resonance imaging (MRI). The presented model includes Kapur’s entropy based segmentation where the optimal threshold values are selected by the use of quantum behaved particle swarm optimization (QPSO) algorithm. The QPSO algorithm incorporates the concept of quantum computing to the PSO algorithm originating from the mechanical aspect that the particle in the space has quantum nature. An extensive experimental analysis portrayed the improved efficiency of the EA-MLTS technique over the compared methods.

Keywords: Image segmentation, Medical images, QPSO algorithm, Kapur’s entropy, NP hard problem

I. INTRODUCTION

A brain cancer denotes a set of anomalous cells, which replicate in the brain in an uncontrollable manner. There are huge variety of brain cancer kinds, which are categorized into 2 classifications, benign (i.e. non-tumorous) are lesser aggressive, slowly created, and most frequently remains separated from nearby brain normal tissues; it doesn’t circulate to other parts of the brain or human body and commonly easy for surgical extract compared to malignancy. Malignant brain tumors (i.e. tumorous) aren't often easier for distinguishing from nearby normal tissues. Thus, it is occasionally complex for extracting them wholly without affecting the nearby brain tissues.

Magnetic Resonance Imaging (MRI) is a non-invasive medical image modal generally utilized in the medical standard since it provides images with higher spatial resolution and contrast among the soft tissues. The MRI gives high data regarding localization, shape, and size of brain cancers for more precise diagnoses and treatment preparation [1, 2]. Consequently, major investigation in medicinal diagnoses and depiction of brain cancers utilizes MRI images. Several MRI series are generated; they are named as weight images, like Fluid Attenuated Inversion Recovery (FLAIR), T1 weight, and T2 weight, Proton-Density Weighted. The T1 weight image gives a better segment for brain tissue because of higher contrast among white and gray matters [3], T1 weighted contrast
improved image and FLAIR are extensively utilized for brain cancer structures diagnosis since it creates cancer part hyper intense.

Precise segments of brain cancers from MRI images denote a challenging and crucial process in diagnoses and treatment preparation. Image segmentation is an active area in medicinal image that involves extracted an image from more than one part creating the field of interest. The Deformable methods are one of the conventional techniques utilized for brain cancer segmentation in MRI images. They are denoted by surfaces (3D) or curves (2D) determined in an image which is moved by the impact of 2 forces namely, local or internal forces specified in the curve to maintain its smoothness in the deformation task when external force is calculated from image data for moving the curve against the object boundary sight. In deformable method, it distinguishes 2 major classifications namely, geometric deformable models and parametric deformable methods or snakes [4]. The parametric deformable method requires a parametric depiction in deformation of the curves. Then, it has complexity in topology modifications for splitting and merging contours into segment multiple objects. The geometric deformable level or model sets presented by [5] moves depending upon geometric measurements like curvature and curve normal. The Brain cancer segmentation contains extract the cancer part from healthier brain tissue; the presence of brain cancers is frequently detected.

The previous investigation operates on the diagnoses of BT by MRI image based on several image processing methods. The innovative MRI investigation process contains a watershed segmentation, neural network (NN) based method [6], fuzzy c-means, clustering technique, edge detection model, Gaussian mixture model, Adaptive Neuro Fuzzy Inference System (ANFIS), multilevel thresholding, heuristic algorithms, and cellular automata. Additionally, [7] emphasized the combination of distinct methods to achieve efficient segment presentation. Besides the NN methods [8, 9], the segmentation methods are modality based methods and achieve proficient with brain MRI register with a particular modality. Deep learning (DL) related models have accomplished challenging performance in massive applications. In DL, the Convolutional Neural Networks (CNNs) plays an important role in computing visual-based issues [14-20].

This paper presents a new evolutionary algorithm based multilevel thresholding based segmentation (EA-MLTS) technique for brain tumor diagnosis. The presented EA-MLTS technique aims to segment the brain tumor using magnetic resonance imaging (MRI). The presented model includes Kapur’s entropy based segmentation where the optimal threshold values are selected by the use of quantum behaved particle swarm optimization (QPSO) algorithm. The QPSO algorithm incorporates the concept of quantum computing to the PSO algorithm originating from the mechanical aspect that the particle in the space has quantum nature. An extensive experimental analysis portrayed the improved efficiency of the EA-MLTS technique over the compared methods.

II. THE PROPOSED EA-MLTS TECHNIQUE

The proposed EA-MLTS technique performs the brain tumor segmentation process using QPSO with Kapur’s entropy technique on MRI images. KE technique is commonly used to segment the medical images [10]. It mainly depends upon the entropy and probability distribution of the image histograms. This model aims to determine the optimum threshold values in such a way that the overall entropy gets maximized. The objective function of KE technique can be represented as:

$$F_{kapur} (th) = H_1 + H_2$$  \hspace{1cm} (1)

where $H_1$ and $H_2$ denotes the entropy and are determined by:

$$H_1 = \sum_{l=1}^{th} \frac{P_{h_l}}{\omega_0} \ln \left( \frac{P_{h_l}}{\omega_0} \right) \text{ and } H_2 = \sum_{l=th+1}^{L} \frac{P_{h_l}}{\omega_1} \ln \left( \frac{P_{h_l}}{\omega_1} \right)$$  \hspace{1cm} (2)

where $P_{h_l}$ is the likelihood distribution of the intensity level, $\omega_0$ (th) and $\omega_1$ (th) are likelihood distribution of the class labels $C_1$ and $C_2$. $\ln(\cdot)$ is the natural logarithm. Alike Otsu’s technique, the entropy based model can be extended for multi-level thresholding where the image can be divided as to k class labels by the use of $k - 1$ threshold values. The objective function can be altered as given below:
\[ F_{Kapur} (TH) = \sum_{i=1}^{k} H_i \]  

where \( TH = [th_1, th_2, th_{(k-1)}] \) is a vector comprising various threshold values. All the entropies are determined individually based on the corresponding \((th)\) value, therefore, Eq. (3) is extended for \( k \) entropy values.

\[ H_k^c = \sum_{i=th_{k+1}}^{L} \frac{P_{h_i}}{\omega_{k-1}} \ln \left( \frac{P_{h_i}}{\omega_{k-1}} \right) \]  

At this point, the probability occurrence \((\omega_0, \omega_1, ..., \omega_{k-1})\) of the \( k \) class, labels are achieved using QPSO algorithm. Fig. 1 illustrates the flowchart of PSO algorithm.

Based on the principle of quantum mechanics, using DELTA significant the PSO technique is employed to the quantum space. The quantum space particle utilized wave function for describing

\[ |\Psi|^2 dx dy dz = Q dx dy dz. \]  

Amongst them, \(|\Psi|^2\) denotes square of the module of wave function, demonstrating the probable density of particle in a location to occur. \( Q \) denotes probable density function and fulfills the normalized state:

\[ \int_{-\infty}^{+\infty} |\Psi|^2 dx dy dz = \int_{-\infty}^{+\infty} Q dx dy dz = 1. \]  

Consider that the \( D \) dimension of (for the dimension of the parameters related with problems) quantum space has a population that comprises of \( n \) particle. The position of the \( it \) particle is \( X_i = (x_{i1}, x_{i2}, ..., x_{iD}) \), and particle by the history of optimum position is \( P_i = (p_{i1}, p_{i2}, ..., p_{iD}) \); eventually, the particle of the optimum historic location is \( P_g = (p_{g1}, p_{g2}, ..., p_{gD}) \).

In quantum space, locations of particle later the particle getting by stochastically stimulating of Monte Carlo dimension:

\[ x_{id} = p_{id} \pm \frac{L}{2} \ln \left( \frac{1}{u} \right) (i = 1,2, ..., n)(d = 1,2, ..., D). \]  

Amongst them, \( u \) denotes arbitrary range number \([0, 1]\). \( L \) is attained through the particle present locations and historic optimum location is \( L = 2 \cdot \beta \left| p_{id} - x_{id} \right| \). Therefore, getting the upgraded equation of quantum PSO:

\[ x_{id}(t + 1) = p_{id} \pm \beta \left| p_{id} - x_{id}(t) \cdot \ln \left( \frac{1}{u} \right) \right|. \]
Amongst them, $t$ represents iteration method counts. $\beta$ denotes contraction expansion factor and variable of quantum PSO. For avoiding the premature convergences, Sun et al. enhanced quantum PSO technique, presenting $m_{best}$ in the method; which is,

$$m_{best} (t) = \frac{1}{n} \sum_{i=1}^{n} p_i (t)$$

$$= \left[ \frac{1}{n} \sum_{i=1}^{n} p_{i1} (t), \frac{1}{n} \sum_{i=1}^{n} p_{i2} (t), \ldots, \frac{1}{n} \sum_{i=1}^{n} p_{iD} (t) \right], \quad (9)$$

Where $p_i$ denotes optimum location of $ith$ particles and $n$ represents particle counts. “$m_{best}$” detects the average optimum position of $n$ particle and resolves problems depending upon the dimensions of parameter.

Afterward the presentation of $m_{best}$, the separate upgraded equation is

$$L = 2 \cdot \beta \cdot |m_{best} - x_{id}|,$$  

$$x_{id} = p_{id} \pm \beta \cdot |m_{best_d} - x_{id}| \cdot \ln \left( \frac{1}{u} \right).$$  

(10)

Then, quantum PSO particle upgrading equation is given by

$$p_{id} = \varphi \cdot p_{id} + (1 - \varphi)p_{gd},$$

$$m_{best} (t) = \frac{1}{n} \sum_{i=1}^{n} p_i (t) = \left[ \frac{1}{n} \sum_{i=1}^{n} p_{i1} (t), \frac{1}{n} \sum_{i=1}^{n} p_{i2} (t), \ldots, \frac{1}{n} \sum_{i=1}^{n} p_{iD} (t) \right].$$
\[ X_i(t + 1) = P_i \pm \beta \cdot |m_{best} - X_i(t)| \cdot \ln \left( \frac{1}{u} \right). \] (11)

Amongst them, \( \varphi \) denotes arbitrary number in \([0, 1]\); other variables are similar to above mentioned one.

III. PERFORMANCE VALIDATION

This section validates the performance of the EA-MLTS technique on the applied BT images [11]. Few sample images are depicted in Fig. 2.

![Sample Images](image_url)

Table 1 and Figs. 3-5 demonstrates the segmentation results obtained by the EA-MLTS technique on the applied five test images with respect to different measures. From the table, it is evident that the presented EA-MLTS technique has accomplished effective performance on all the applied images. For the applied test image 1, the EA-MLTS technique has obtained a MSE of 0.132, RMSE of 0.363, PSNR of 57.35dB, JI of 0.878, and accuracy of 97.81\%. Moreover, on applied test image 2, the EA-MLTS model has attained a MSE of 0.102, RMSE of 0.319, PSNR of 57.87dB, JI of 0.845, and accuracy of 97.87\%.

<table>
<thead>
<tr>
<th>No. of Images</th>
<th>MSE</th>
<th>RMSE</th>
<th>PSNR</th>
<th>JI</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>0.132</td>
<td>0.363</td>
<td>57.35</td>
<td>0.878</td>
<td>97.81</td>
</tr>
<tr>
<td>Image 2</td>
<td>0.102</td>
<td>0.319</td>
<td>57.87</td>
<td>0.845</td>
<td>97.87</td>
</tr>
<tr>
<td>Image 3</td>
<td>0.143</td>
<td>0.378</td>
<td>57.70</td>
<td>0.841</td>
<td>97.09</td>
</tr>
<tr>
<td>Image 4</td>
<td>0.113</td>
<td>0.336</td>
<td>58.92</td>
<td>0.867</td>
<td>97.76</td>
</tr>
<tr>
<td>Image 5</td>
<td>0.076</td>
<td>0.276</td>
<td>59.72</td>
<td>0.890</td>
<td>98.42</td>
</tr>
<tr>
<td>Average</td>
<td>0.110</td>
<td>0.330</td>
<td>58.31</td>
<td>0.860</td>
<td>97.79</td>
</tr>
</tbody>
</table>

![Fig. 2. Sample Images](image_url)
Fig. 3. MSE and RMSE analysis of EA-MLTS model

Fig. 4. PSNR analysis of EA-MLTS model
Furthermore, on applied test image 3, the EA-MLTS approach has achieved a MSE of 0.143, RMSE of 0.378, PSNR of 57.70dB, JI of 0.841, and accuracy of 97.09%. Additionally, on applied test image 4, the EA-MLTS algorithm has obtained a MSE of 0.113, RMSE of 0.336, PSNR of 58.92dB, JI of 0.867, and accuracy of 97.76%. In line with, on applied test image 5, the EA-MLTS model has attained a MSE of 0.076, RMSE of 0.276, PSNR of 59.72dB, JI of 0.890, and accuracy of 98.42%.

**Table 2** Segmentation Results of Proposed EA-MLTS with state of arts methods in terms of PSNR and JI

<table>
<thead>
<tr>
<th>Methods</th>
<th>PSNR (dB)</th>
<th>JI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed EA-MLTS</td>
<td>58.310</td>
<td>0.860</td>
</tr>
<tr>
<td>Optimal-KE</td>
<td>57.481</td>
<td>0.859</td>
</tr>
<tr>
<td>TLBO-Kapurs</td>
<td>15.718</td>
<td>0.771</td>
</tr>
<tr>
<td>TLBO-Tsallis</td>
<td>15.321</td>
<td>0.742</td>
</tr>
<tr>
<td>TLBO-Shannon</td>
<td>26.340</td>
<td>0.837</td>
</tr>
</tbody>
</table>

Table 2 and Figs. 6-7 investigates the comparative results analysis of the EA-MLTS with existing methods interms of PSNR and JI [12, 13]. The obtained results portrayed that the EA-MLTS technique has outperformed the other methods by accomplishing a higher PSNR of 58.310dB and JI of 0.860.
Fig. 6. Comparative analysis of EA-MLTS model in terms of PSNR

Fig. 7. Comparative analysis of EA-MLTS model in terms of JI

At the same time, it is observed that the TLBO-Tsallis method has obtained least performance with the PSNR of 15.321dB and JI of 0.742. Besides, the TLBO-Kapur’s technique has attained slightly enhanced outcome with the PSNR of 15.321dB and 0.742 JI. Moreover, the TLBO-Shannon model has depicted moderate results with the PSNR of 26.340dB and JI of 0.837. Though the Optimal-KE model has showcased near optimal outcomes with the PSNR of 57.481dB and JI of 0.859, the presented EA-MLTS technique has demonstrated maximum segmentation efficiency.
IV. CONCLUSION

This paper has introduced a new EA-MLTS technique for brain tumor segmentation. The presented EA-MLTS technique aims to segment the brain tumor using magnetic resonance imaging (MRI). The presented model includes Kapur’s entropy based segmentation where the optimal threshold values are selected by the use of QPSO algorithm. The QPSO algorithm incorporates the concept of quantum computing to the PSO algorithm originating from the mechanical aspect that the particle in the space has quantum nature. An extensive experimental analysis portrayed the improved efficiency of the EA-MLTS technique over the compared methods. The obtained simulation results pointed out that the EA-MLTS technique has outperformed the existing methods by obtaining a minimal MSE of 0.110 and maximum accuracy of 97.79% As a part of future scope, the segmentation results can be further improved by the use of DL techniques.

REFERENCES

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