Fuzzy Level Set Search and Rescue Optimization (FLSSR) Based Segmentation of Pediatric Brain Tumor

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Abstract. Brain tumor disease in children is deadly due to unrecognition at early stage. Hence, a accurate, and less affluent method to detect pediatric brain tumor is necessary. In this paper the theme of model is characterized with stages like Preprocessing and then segmentation of the MRI image by fuzzy level set search and rescue optimization (FLSSR) for an accurate segmentation with high speed and less complexity.

Keywords: CNN · paediatric MRI image · wavelet transform · fuzzy level set · brain tumor

1 Introduction

Brain tumor is a solid tumor which commonly found in pediatric area. The treatment and analysis of brain tumor are based on various factors like age of the patient, position and tumor type. The grade and type of the brain tumor are analyzed with the help of surgical resection method [1, 2]. The surgical resection method provides better analysis and commonly used for various tumor [3]. A pre-reactive analysis make impact on clinical resection and provide adjuvant treatment. A conventional MRI is commonly used for tumor analysis which gives lower accuracy performance [4]. The utilization of MRI increased in the tumor diagnosis field for the previous years, especially in pediatric area. There are various factors like apparatus breakdown and medication feedback causes adversarial events in MRI measurement which act as imaging modality [5]. The tumor occurrence and corresponding risk elements act as important factor for the execution of evidence-based quality development events.

The second cause of pediatric cancer is the pediatric brain tumors which is the leading cause of cancer mortality in children [6, 7]. The major symptom of pediatric brain tumors is occurrence of seizures inside the brain and happens sometime among birth or until they(children) reach the age of 15 [8]. After leukemia, 15% of pediatric cancer is brain cancer. There are four types of brain tumors such as Ependymoma (EP),

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Medulloblastoma (MB), Pilocytic (PILO) and Diffuse Intrinsic Pontine Glioma (DIPG). Various treatment and prediction approaches are included in these type of tumors [9]. Type of tumor identification is extremely appreciated without the required of surgery. The MRI is most commonly used technique for analysing cancer [10].

Our contributions are given below:

- To identify efficient approaches to handle MRI data for pediatric brain tumor patients.
- To develop the new fuzzy based search and rescue algorithm for an effective segmentation of brain MRI.

2 Related Work

Gayathri et al. [11] suggested a cranial closure assessment on pediatric MRI. During cranial closure imaging technique, CT with 3D reformat applied and used to estimate abnormalities of the brain. The proposed work utilized for calculating the consistency of MRI and CT (Computed Tomography). More than 500 sequential patients are experienced in CT and MRI study. With the help of pediatric neuroradiologist MRI was studied and estimate sagittal, lambdoid sutures and coronal. After the analysis MRI gives better accuracy than CT.

Christine et al. [12] developed a structural brain MRI investigation of pediatric cancer survivors handled with chemotherapy. The cortical thickness, subcortical volumes and morphometry are used as metrics of MRI. The influence of chemotherapy was studied in survivors with non-central nervous structure cancers. Along with functioning memory tasks, evaluations of executive operational behaviour and manual dexterity events are interrelated. The proposed methodology proved that oncology patients show bargain morphometry and cortical thickness which are associated with events of manual dexterity, executive operational behaviour and occupied memory scores.

Michaela et al. [13] developed automated estimation model of imaging biomarker for POPCMS (Post-Operative Cerebellar Mutism Syndrome). The POPCMS occurred within the cerebellum and brain stem. The 2D analysis was limited due to the non-volumetric nature of frequency and leads to complexity in inter-subject and intra-subject analysis. To overcome these issues, computerised image processing and pipeline investigation was introduced. The 4D volumetric MRI database used for offer longitudinal depiction of the brainstem and cerebellum at particular interval points.

Orman et al. [14] proposed progressive method of neuroimaging with MRI and CT. The introduced method discussed about the 17-year patient and he suffered from changes in mental status. During the neuroimaging studies a thrombosed aneurysm was exposed with CT and MRI along with critical left MCA (Middle Cerebral Artery) stroke. Due to the irregularities in SWI(Susceptibility) and DWI (Diffusion Weighted) corresponding with the PWI (Perfusion Weighted Imaging) an ischemic penumbra was recognized.

Ericka et al. [15] discussed the use of brain MRI and spectroscopy for consequence prediction. The proposed method used spectroscopy and brain MRI as forecasters of disability and death. The MRI information was utilized for clinical analysis. The neurological and mortality results were evaluated. The nonparametric tests were employed for the verification of connection between MRI or spectroscopy.

The paediatric brain tumor caused due to the abnormal growth of cells inside the child's brain. Benign and Malignant are the major types of pediatric brain tumors. The chance of recovery and treatment are based on several factors like tumor type, tumor position, tumor spreading nature and child age. Due to the technological development, innovative treatments are established and used at different stages of diagnosis. The pediatric brain tumor treatment is difficult when it compared to adult cases. The cause of tumor is not clear in most children with primary brain tumors. Ependymoma and Medulloblastoma are the major tumor type in pediatric area. The risk of brain tumors increased in some children by family history of genetic syndromes. The supervised learning approaches need labelled information that is costly to accumulate and there is a severe lack of pediatric brain tumor MRI information. Hence, new optimized deep convolutional neural network introduced for the classification of brain images in child's brain.

3 Proposed Methodology

The proposed method undergoes two steps Pre-processing & Segmentation. Initially pediatric MRI data is pre-processed with Extended Adaptive Weiner filter (EAWF) and the tumor portions are segmented using fuzzy search and rescue optimizer. By this concept, we can identify and point out tumor portions. The frame work of proposed methodology is shown in Fig. 1.

3.1 Preprocessing

The initial step followed by our suggested work is pre-processing. Provision of MRI images are given as an input due to its enormous information regarding pediatric MRI data. In a pre-processing stage, the quality of image get enhanced by making it sharper and detach the presence of horrible noise in an image. The superiority of visual appearance and image quality can be recognized by the pre-processing stage. Filtering process will upgrade the oncoming stage such like segmentation. The dominant filter technique i.e. Extended Adaptive Wiener Filter (EAWF) filter to progress the image clarity by eliminating the noises. Visualization of MRI images with good appearance can be maintained by the elimination of unwanted noises. In order to extend the adaptive Wiener Filter, replacement of dispersion index instead of variance has been initiated.

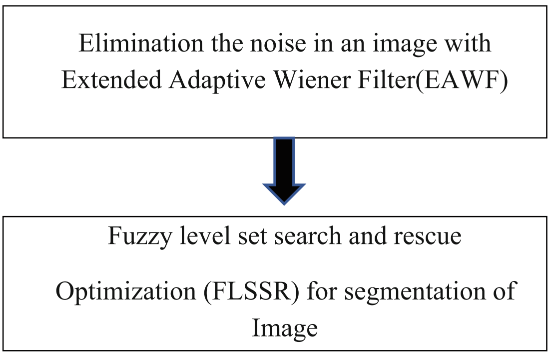


Fig. 1. Frame work of proposed methodology

The use of EAWF filter diminishes any kind of noise recognized in the image along with improving the quality of an image. Let us consider as a pixel location for an input image. In AWF the determination of noise can be done based on mean and noise variance. But the Extended AWF filter utilizes dispersion index to detect the noise from the image. The standard expression of dispersion index can be displayed as:

$$d_i = \frac{\sigma^2}{\mu} \tag{1}$$

If the dispersion index is applied to the AWF filter, the general filter equation get revised like the following:

$$EAW_f\left[X_p(\rho_1,\ \rho_2)\right] = \mu + \frac{d_i - \sigma_n^2}{d_i}\left[X_p(\rho_1,\ \rho_2) - \mu\right] \tag{2}$$

The efficient output after pre-processing can be defined determined through the following formula:

$$EAW_f\left[X_\rho(\rho_1,\ \rho_2)\right] = X_\rho(p_1,\ p_2) - \mu\left(\frac{\sigma_n^2}{\sigma^2}\left[X_\rho(\rho_1,\ \rho_2) - \mu\right]\right) \tag{3}$$

where designates the mean value and specifies the variance of noise.

The enhanced quality of MRI image can be detected based on Eq. (3). The presence of noise in an MRI image can be tackled by using the suggested EAWF filter. Noise reduction enhance the quality of an image as well as the image appearance is visible and more coherent than the original image. The primary aim of the introduced filter is to remove the speckle noise present in MRI image and it occurs due to the movement of patients and environmental conditions. AWF filter eradicates the speckle noise resourcefully, meanwhile enlightening the image quality.

3.2 Fuzzy Level Set Search and Rescue Optimization (FLSSR) for Segmentation Process:

Segmentation of brain tumor potions can be emphasized by fuzzy level set optimization strategy. Similar to edge parameter representation, fuzzy level set utilizes partial differential equation $f\ (t,\ u, v)$ to represent the outlier portions. After tracking the fuzzy level set zero, we obtain an $L\,(t)$ implicit function to validate the outliers in the edges. The implicit function can be expressed as:

$$\left\{\begin{array}{lll} \Phi\,(t, u, v) & < 0 & (u, v)\ in\ L\,(t) \\ \Phi\,(t, u, v) & = 0 & (u, v)\ on\ L\,(t) \\ \Phi\,(t, u, v) & > 0 & (u, v)\ to\ L\,(t) \end{array}\right\} \tag{4}$$

Edge indicator function is established based on the regulation of driving force to prevent the optimal solutioin a fuzzy level set method and it is defined as:

$$e = \frac{1}{1 + \left|\Delta\,(K_\sigma\ *\ I)\right|^2} \tag{5}$$

I denotes the MRI pediatric image, K_σ indicates smooth gauss kernel and Δ represents the gradient operation of MRI image. The differential partition equation of fuzzy level set method can expressed as:

$$\frac{\partial \phi}{\partial t} = e \, |\Delta\phi| \left[div \left(\frac{\Delta\phi}{|\Delta\phi|} \right) + \upsilon \right] \tag{6}$$

$div \left(\frac{\Delta\phi}{|\Delta\phi|} \right)$ denotes the average curvature. Meanwhile, the computational complexity is one of the short coming in an fuzzy level set approach also it extends the two level segmentation problems in to three level segmentation problem. However in order to overcome the complexity issue search and rescue is implemented in fuzzy approach.

The primary aim of this stage is tumor segmentation from MRI images. In accordance with our proposed approach, brain tumor segmentation problem is defined as the position of human which is equivalent to the solution of optimization problem and the importance of clue is termed as best optimal solution. Brain tumor segmentation is emphasized as an optimization problem in SA [16] optimization. The procedure of the suggested approach is processed below:

Clues: The information of clues are gathered by group members during the search operation. The group members with problem dimension is indicated as along with this the dimension matrix is corresponding to. Disseminate of clues indicates the outlier boundary of an MRI image. Initially, the position of founded clues are randomly placed in a clue matrix and it is defined as:

$$CM = \begin{bmatrix} Q \\ P \end{bmatrix} = \begin{bmatrix} Q_{11} & \cdots & Q_{1d} \\ \vdots & \ddots & \vdots \\ Q_{n1} & \cdots & Q_{nd} \\ P_{11} & \cdots & P_{1d} \\ \vdots & \cdots & \vdots \\ P_{n1} & \cdots & P_{nd} \end{bmatrix} \tag{7}$$

Based on the random initialization of clue matrix, generation of new solutions takes place in both social and individual stages. Updation of matrices such as Q, P, CM are evaluated in each search stages. The matrices Q, P denotes the memory and position of humans. Human stages namely, social and individual are preceded as follows:

Social stage: In a social stage, the search direction is procured according to the following equation:

$$SD_j = (Q_j - CM_i) \quad i \neq j \tag{8}$$

Q_j and CM_i symbolize the position of both human and clues also, the search direction of j^{th} human is indicated as SD_j. i represent the random integer number and it lies between the range of 1 and 2. The expression of social stage is defined as:

$$Q_{j,w} = \begin{cases} \begin{pmatrix} CM_{i,w} + R_1 \times (Q_{i,w} - CM_{i,w}) \; if \; F(CM_i) > F(Q_j) \\ Q_{i,w} + R_2 \times (Q_{i,w} - CM_{i,w}) \qquad otherwisw \end{pmatrix} \\ Q_{i,w} \end{cases}$$

$$\begin{matrix} if\ R_2 < AB\ or\ w = w_{random}\ w = 1, 2, \ldots d \\ otherwise \end{matrix}, \tag{9}$$

The above equation attains new position in each dimension. For (j^{th}) human and $\left(i^{th}\right)$ clue, the new position based on (W^{th}) dimension can be expressed as $Q_{j,w}$ and $CM_{i,w}$. The random numbers R_1 and R_2 lies between the interval of (−1, 1) and (0, 1). The random variable R_1 remains fixed and R_2 get jumbled in all dimensions. The parameter AB ranges between 0 and 1. The values of objective function can be expressed as $F\ (CM_i)$ and $F\left(Q_j\right)$.

Individual stage: The new position of (j^{th}) human can be obtained by the following equation

$$Q\prime_j = Q_j + R_3 \times (CM_i - CM_n) \qquad j \neq i \neq n \tag{10}$$

The movement along other clues are prevented by the selection of random integers i and j. The random integer R_3 in individual stage ranges between 0 and 1.

Boundary Control: The solutions of individual and social stage are obtained based on the location of solution space. The new position in accordance with (j^{th}) human can be customized by Eq. (11).

$$Q_{j,k}\prime = \left\{ \begin{matrix} \left(Q_{j,k} + Q_k^{\max}/2\right) & if\ Q_{j,k}\prime > Q_k^{\max} \\ \left(Q_{j,k} + Q_k^{\min}/2\right) & if\ Q_{j,k}\prime > Q_k^{\min} \end{matrix} \right\} W = 1, ...d \tag{11}$$

$Q_k^{\max}$ and $Q_k^{\min}$ denotes the maximum and minimum threshold values for (W^{th}) dimension.

Information and Position Updation: Based on individual and social stages, searching process done by group members for each iterations. If the position of objective function $Q_j\prime\left(F\left(Q_j\right)\right)$ is greater than $F\left(Q_j\right)$, the memory matrix P accumulates the previous position Q_j with the aid of Eq. (12).

$$P_m = \begin{cases} Q_j\ if\ F(Q_j') > (Q_j) \\ P_m \quad otherwise \end{cases} \tag{12}$$

$$Q_m = \begin{cases} Q_j'\ if\ F(Q_j') > (Q_j) \\ Q_j \quad otherwise \end{cases} \tag{13}$$

Abandoning Clues: In search and rescue optimization, time plays an essential role. The operation searches an enormous space within a short period of time. If the searching process get delayed, the rescue teams will fall in to a critical position. If the search agent is unable to determine new solution under few iterations, then it go towards the current position to new position. Initially, the unsuccessful search agent S is set to zero to determine crucial clues. The fitness function can be evaluated based on following equation:

$$S_j = \begin{cases} S' + 1_j\ if\ F(Q_j') \\ 0 \quad otherwise \end{cases} \tag{14}$$

Constraint Managing Mechanism: In this, the penalty function is used to solve the optimization problem. The memory, position and S_j are updated based on the following equations which are as follows:

$$P_m = \begin{cases} Q'_j \;\; if\ Q'_j\ is\ better\ than\ Q_j \\ P_m\ otherwise \end{cases} \tag{15}$$

$$Q_j = \begin{cases} Q'_j\ if\ Q'_j\ is\ better\ than\ Q_j \\ Q_j\ otherwise \end{cases} \tag{16}$$

$$S_j = \begin{cases} 0 \qquad\quad if\ Q'_j\ is\ better\ than\ Q_j \\ S'_j + 1\ otherwise \end{cases} \tag{17}$$

After the updation, Restart mechanism takes place to randomly generate matrices namely human and memory. The fuzzy optimization strategy segment the pediatric MRI brain image for further analysis of an image.

4 Results and Discussions

The proposed pediatric brain tumour classification (PBTC) model is examined with regard of five phases (pre-processing, segmentation) In the pre-processing stage, by the intrusion of EAWF filtering technique the quality of image get enhanced and the horrible nose in image are eradicated. The maintenance of good quality images are done in the first stage. The second stage of proposed model is segmentation. The need of segmentation will provide an accurate classification results and this can be done by FLSSR segmentation technique.

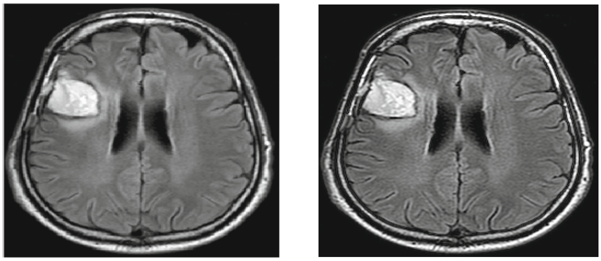
5 Performance Evaluation

Stage 1: Pre-processing

The collected images are corrupted with impulsive noise and the removal of noise is done by stage 1 (pre-processing).To diminish the inadequacies of the image, the stage of pre-processing is essential. The method of pre-processing helps to enhance the visual appearance and quality of an image. The accuracy of an image gets degrade due to the presence of noise. The pre-processing stage helps to rise up the upcoming stages such as segmentation, feature extraction, feature selection and classification. The filtered image is shown in Fig. 2.

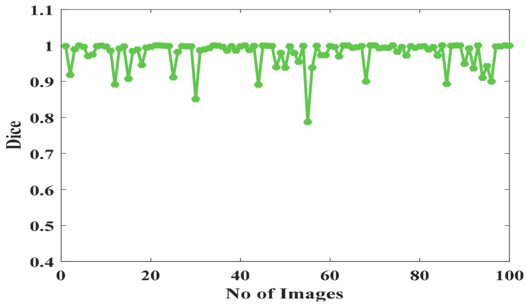
Stage 2: Segmentation

For a segmented tumour region, the performance measures of dice similarity coefficient and jaccard coefficients are evaluated. The fuzzy level set optimization approach is intended to segment the tumour region in the collected pediatric MRI image. To balance the computational complexity of the fuzzy level set strategy, the rescue optimization is emphasised to point out the tumour region with high speed and less complexity. Dice and jaccard is termed as a spatial overlapped index and also a reproducibility validation metrics. The metrics of dice and jaccard ranges from 0 to1 and it measures the similarity

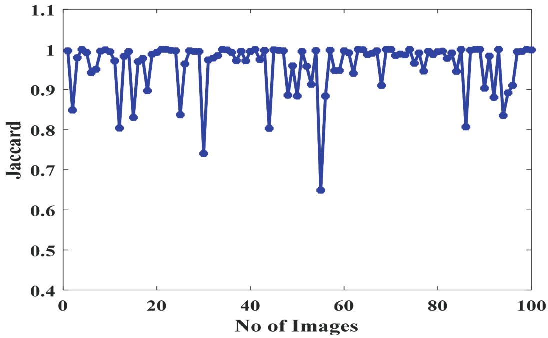


Input image Filtered image

Fig. 2. Pre-processed image



(a)



(b)

Fig. 3. Performance measure of segmentation (3a) Dice similarity coefficient, (3b) Jaccard coefficient

between two images. The range 0 explicate that the no spatial overlap (low) among two images and 1 elucidates high overlap.

$$Dice\,(p, q) = \frac{2\,|P_1 \cap q_1|}{|p_1 + q_1|} \tag{18}$$

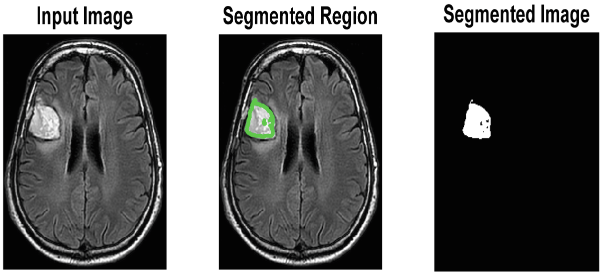


Fig. 4. Segmented image

$$Jaccard\ (p, q) = \frac{P_1 \cap q_1}{p_1 \cup q_1} \tag{19}$$

The process of segmentation is to partitioning the images in to dissimilar sections. In above equation, ∩ ensembles the logical AND operator. p, q denotes the collected pediatric brain tumour image. Figure 3 illustrates the dice and jaccard similarity coefficient for the proposed segmentation approach under 100 pediatric images. From figure it is observed that it lies between 0.9 to1 and it almost reaches 1. Zero represents imperfect matching and one represents perfect matching. The tumour segmented image is shown in Fig. 4.

6 Conclusion

The major aim of this research is to accomplish an effective child tumour classification system that can be reliable with less computational time and high accuracy. The research is progressed with two stages namely pre-processing, segmentation. The raw input pediatric MRI image is filtered with the assistance of EAWF filtering technique and it upsurge the clarity of an image. After pre-processing, the feature extraction is proceeded for an accurate pediatric tumour segmentation and this can be terminated by FLSSR strategy.

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