Identification of high grade and low grade tumors in MR Brain Image using Modified Monkey Search Algorithm

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Abstract. Detection of tumors present in the Magnetic Resonance brain image is a challenging task in the research field of medical imaging processing. The tumors with distinguished boundaries are difficult to find in the MR brain images, while performing the manual segmentation process. There is a necessity of an automated segmentation technique for performing better segmentation in terms of tumors with distinguished boundaries. The automated modified monkey search technique is used to find the optimized cluster position, and a random search operation is performed to locate all the pixels present in the image and then finally the location of the tumor region is exactly segmented/predicted by using the suggested monkey search algorithm. The suggested technique will support the radiologist for finding the tumors with distinguishing boundaries and accuracy of prediction of tumors is also improved lot with this approach. Based on the early prediction of tumors, diagnosing procedures will save the lives of many human beings.

Keywords:

1. Introduction

A brain tumor leads to the accumulation/growth of abnormal cells in your human brain. Based on the severity, the tumors can be classified into several types. The tumors in the beginning stage/less antagonistic are called benign (non-cancerous) and also some types of tumors begin in the brain are called primary tumors. Second type of tumor is more antagonistic called as malignant (cancerous) [1]. The tumors spread from other parts of the body and migrate to the human brain are called metastatic tumors. Based on the growth rate, size and location of the tumor, the treatment of brain tumors can be applied [2].

Magnetic Resonance Imaging (MRI) is one of the imaging technologies to diagnose the tumors in the human brain. MRI uses less ionization radiation that produces three-dimensional anatomical structures of the human brain [3]. The human brain is made of soft tissues; the MRI scanner is one of the best techniques to visualize the soft tissue of the brain. The grey, white matter and Cerebrospinal Fluid (CSF) present in the image is clearly examined with the help of MRI techniques that can be used to examine/diagnose the tumor [4&6].

MRI produces different types of imaging sequences; T1-W (weighted) image is produced using a short time to echo (TE) and time to response (TR) time for determining the contrast and brightness of the image for assessing the fat content in the image. In T2-W (weighted) image is produced using a long time to echo (TE) and time to response (TR) time for...
accessing the Fat and water content look bright [7]. Fluid Attenuated Inversion Recovery (FLAIR) uses the inversion recovery sequence for surprising the cerebrospinal fluid and similar to the T2-weighted image and grey matter present in the image looks brighter than the white matter, CSF content looks dark instead of the bright [9].

For segmenting the tumors with complex structures, there is a need of automated algorithm. The proposed automated modified monkey search algorithm identifies the tumors all different sequence images in the MR brain image.

2. Related Works

Crawford et al. [10] suggested the binary search techniques for solving the set cover problem. This process used the behaviour of monkey for climbing mountain to produce the global optimum solution for set the covering problems. Based on finding the decision the minimum feasible cost for solving the problem is provided.

Ma et al. [16] used the random forest method for the demarcation of brain tumors. Both local and contextual information is used for the locating brain tumor and tissue in the MR image. The structural information is associated with the connected and concentrated random forest for analyzing then structure. Peak values of the pixel are obtained using the active contour method, then clustering of similar pixels is grouped. The proposed systems delivered promise segmentation results, the proposed model requires the number of training labels in the initial stage.

Zhou et al. [31] proposed the framework for the segmentation of brain tumors based on the multi-task networks with cross guided attenuation. The complete tumor region is detected using the region of interest (ROI) and then the network is trained based on the patches (tissue, tumor and background). Training sample is dilated with the ground truth image of the complete core area of tumor. Based on the cross guided information selected to learn the attenuation of channel, the accuracy of segmentation results varied on the output.

Tong et al. [28] used the sparse kernel coding for performing the segmentation of tumors in multi-sequence images. The peak level of a pixel is found using the entropy-based process and then the clustering of the similar pixel in the input image. The tumors with the distinguished boundaries in MR brain images are difficult to segment.

Razzak et al. [22] suggested the convolutional neural networks (CNN) based on multi-scale two way-path for brain tumor diagnosis in the MR brain. The two-way path neural networks are used to reduce the inconsistency and over-fitting parameters involved in the process. Novel deep learning approached used the global information for the segmentation process but the way path neural networks use the local information for performing the segmentation task in a fast manner. The performance of CNN is improved based on tuning the numbers of parameters and reliability of model.

Pereira et al. [19] utilized the concepts of convolutional neural networks (CNN) for the segmentation of brain tumors. The framework is designed using 3 * 3 kernels, then the model is trained by assigning the weights to the convolutional layers and features of a kernel are mapped with kernel assigned. Dependent upon the features extracted, the kernel is convoluted over the image and neighborhood information is considered for the clustering process. Even a large set of feature maps is used in the CNN architecture, delivered the lower performance based on the selection of activation function used for the process.

Alagarsamy et al. [5] suggested the BAT based Interval fuzzy techniques for segmenting the tumor and tissue in MR brain image. The initial position of the pixel is selected in a random manner and then the cluster position is determined by using the BAT algorithm, clustering process is performed using the interval fuzzy clustering. The accuracy of segmentation for high grade and low-grade tumors can be improved.

Bai et al. [8] used the clustering process based on the Fuzzy C-Means for segmenting the high-grade tumors. The spatial information is defined to find out the pixel present in the input image and the uncertainties of the image are found by using the fuzzy membership function. The
clustering process of suggested techniques is performed based on local information. The accuracy of the recommended techniques can further improved.

Zhang et al [30] suggested the longitudinally guided super-resolution algorithm for finding the tumors present in the infant brain image. Longitudinally regularization is used to examine the anatomical structure of brain combined with bilateral filtering process to find the optimum solution. The pixels from more than clusters lead to degrading the performance of the segmentation process.

Tang et al. [27] recommended the segmentation based on multi-atlas (MAS) for low graded tumors. MMS framework produces more accurate results for the MR brain image. Two-step process is used for the prediction; first, the information of the normal brain is recovered using the low-rank method and then mapping of the registered atlas with the recovered images. The limitation of the proposed technique is that tumors with discriminative appearance difficult to segment.

After analyzing the related works based on the segmentation of tumors, finally concluded that this type of combination does not exist. The modified monkey search (MMS) technique is proposed in the application of the medical field.

**Figure 1:** Flowchart of proposed modified monkey search algorithm

After analyzing the related works based on the segmentation of tumors, finally concluded that this type of combination does not exist. The modified monkey search (MMS) technique is proposed in the application of the medical field.
3. Proposed Methodology

The monkey algorithm shown in fig 1 is one of the meta-heuristics algorithms inspired by the behaviors of the mountain climbing process of monkey to solve the multimodal optimization problem. The process of the monkey algorithm is classified into three steps: Climb process, watch-jump process and somersault process [11]. The Climb process deals with finding the optimal solution for the searching process; the pseudo gradient function for objective function is used to search the optimal solution for the problem. The intention of the somersault process is used to find the new optimal solution, if the new optimal solution is better than the old one then the updated position will be updated [12 & 29]. In the modified monkey search algorithm, first, the initialization of the population generated in a random manner. Then, the best cluster centroid is calculated using a search operator for all (Q) components. Second, the climbing process of the monkey step is used to find the best position towards the objective function. Finally, the jump process is used to search similar pixels in the image for the clustering process. This process leads to segment the tumor portion in the input MR brain slices.

Monkey Search Algorithm

Step 1: Solution Representation: The initial population of monkey (Q), for all monkey i ∈ {1,2,..,Q} size and vectors are defined by vector \( y_i = \{ y_{i1}, y_{i2}, ..., y_{in} \} \) which denotes the solution for the optimization problem.

Step 2: Initialization of population: The initial population of monkey is randomly generated.

Step 3: Process of Climb: The random vector \( \Delta y_i = \{ \Delta y_{i1}, \Delta y_{i2}, ..., \Delta y_{in} \} \), which express the optimized solution for problem.

Step 4: Objective function:

\[
 f_{ij}(y_i) = \frac{f(y_i+\Delta y_i)-f(y_i)}{2\Delta y_i} \tag{1}
\]

Where \( j=1,2,...n \) in the equation (1) for each vector.

Step 5: Pseudo gradient function: The Pseudo gradient function for objective function at point \( y_i \) is defined by equation (2)

\[
 f_i(y_j) = (f_{i1}(y_{i1}), f_{i2}(y_{i2}), f_{in}(y_{in})) \tag{2}
\]

Step 6: Assign \( Z_j = y_{ij} + \alpha \text{ sign}(f_i(y_j)) \), where \( j = 1,2,...n \) and \( z = \{ z_1, z_2, ..., z_n \} \)

Step 7: The feasible solution for \( Z_i \) is provided by assigning \( y_i \rightleftharpoons z \), otherwise keep the old position of \( y_i \).

Step 8: Repeat the Step 3 to 7 until the objective function is minimized to produce the optimize solutions.

Step 9: Watch-Jump Process: The maximum distance of monkey can watch and jump for the random generated number is calculated from \( \{ y_{ij} - b, y_{ij} + b \} \), where \( j = 1,2,...n \) and \( b \) represents the eye sight of the monkey.

Step 10: Assign \( y_i \rightleftharpoons z \) endow with \( f(z) \geq f(y) \), in case z solution is feasible. Otherwise the process is repeated until the feasible cluster position z value is found, in anticipation of all the pixels is visited.

Step 11: Somersault process: The real number (θ) and set \( Z_i = y_{ij} + \theta (p_j - y_{ij}) \)

\[
 p_j = \frac{1}{N} \sum_{i=1}^{N} y_{ij} \tag{3}
\]

Where \( j = 1,2,...n \) and \( p = (p_1, p_2, ..., p_n) \) is denoted as pivot element of somersault process and direction of monkey is represented as \( p_j - y_{ij} \).

Step 12: Assign \( y_i \rightleftharpoons z \) if \( z = \{ z_1, z_2, ..., z_n \} \) for getting the feasible solution, otherwise step 11 and step 12, is repeated until the feasible \( z \) value is found.
Step 13: **Termination:** Finally the above said process is repeated until the stopping criteria are going to satisfied.

4. **Results and Discussion**

The dataset consists of both low-grade and high-grade tumors from BRATS 2015 repository is used for the evaluation process of the proposed modified monkey search algorithm. Tumors with different grades and various sequences of images have been considered for the evaluation process. Table 1 accumulates the variable and parameters used in the proposed system.

| S.No | Parameters | Functioning of parameters |
|------|------------|---------------------------|
| 1    | $Q$        | Initial population of monkey. |
| 2    | $\Delta y_i$ | Random vector. |
| 3    | $f_{ij}(y_i)$ | Objective function. |
| 4    | $f_i(y_i)$ | Pseudo gradient function. |
| 5    | $\theta$ | Real number. |
| 6    | $p$ | Pivot element of somersault process. |

The efficiency of the suggested modified monkey search (MMS) algorithm in demarcating the input MR brain slices is assessed using the DOI and computational time denoted in the table 2.

| S.NO | Input Image | DOI Value | Computational time |
|------|-------------|-----------|--------------------|
| 1    | L1          | 95.12     | 1.123              |
| 2    | L2          | 96.26     | 1.324              |
| 3    | L3          | 95.59     | 1.426              |
| 4    | L4          | 96.12     | 1.324              |
| 5    | L5          | 96.03     | 1.024              |
| 6    | L6          | 95.02     | 1.324              |
| 7    | L7          | 95.12     | 1.024              |
| 8    | L8          | 95.21     | 1.326              |
| 9    | L9          | 95.03     | 1.114              |
| 10   | L10         | 95.12     | 1.024              |
| 11   | L11         | 95.12     | 1.123              |
| 12   | L12         | 96.26     | 1.324              |
| 13   | L13         | 95.59     | 1.024              |
| 14   | H1          | 96.12     | 1.324              |
| 15   | H2          | 96.03     | 1.024              |
| 16   | H3          | 95.02     | 1.324              |
| 17   | H4          | 95.12     | 1.024              |
| 18   | H5          | 95.21     | 1.326              |
| 19   | H6          | 95.03     | 1.114              |
| 20   | H7          | 95.12     | 1.024              |
| 21   | H8          | 95.12     | 1.324              |
The segmentation efficiency of high-grade tumors present in the input MR brain slices is shown in the figure 2.

| Type | Input Image | Modified Monkey Search Algorithm | Identified tumor Region | Brats ground truth Image |
|------|-------------|----------------------------------|-------------------------|-------------------------|
| L1   | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) |
| L2   | ![Image](image5.png) | ![Image](image6.png) | ![Image](image7.png) | ![Image](image8.png) |
| L3   | ![Image](image9.png) | ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |
| L4   | ![Image](image13.png) | ![Image](image14.png) | ![Image](image15.png) | ![Image](image16.png) |
| L5   | ![Image](image17.png) | ![Image](image18.png) | ![Image](image19.png) | ![Image](image20.png) |
| L6   | ![Image](image21.png) | ![Image](image22.png) | ![Image](image23.png) | ![Image](image24.png) |
Figure 2: Segmentation results obtained by Modified Monkey Search Algorithm for low-grade tumors.
Different sequences of MR Brain slices with the low-grade tumors have been considered for the effective validation of the proposed MMS techniques along with the ground truth available in the BRATS repository. The suggested algorithm has made speculative segmentation results by identifying the exact tumor region in the input MR brain image. The proper separation between the tumor and other regions are explicitly easily accessed with the support of the modified monkey search techniques. Tumors present in the various location and the boundaries are exactly distinguished with the aid of the proposed algorithm. Some exigent cases with serial numbers such as L2, L3, L7, L9, L12 of Figure.2 have been conspicuously demarcated by the proposed techniques. Finally, the segmented results of recommended MMS techniques are compared with the ground truth.

| Type | Input Image | Modified Monkey Search Algorithm | Identified tumor Region | Brats ground truth Image |
|------|-------------|----------------------------------|-------------------------|-------------------------|
| H1   | ![Image](image1.png) | ![Image](image2.png) | ![Image](image3.png) | ![Image](image4.png) |
| H2   | ![Image](image5.png) | ![Image](image6.png) | ![Image](image7.png) | ![Image](image8.png) |
| H3   | ![Image](image9.png) | ![Image](image10.png) | ![Image](image11.png) | ![Image](image12.png) |
| H4   | ![Image](image13.png) | ![Image](image14.png) | ![Image](image15.png) | ![Image](image16.png) |
| H5   | ![Image](image17.png) | ![Image](image18.png) | ![Image](image19.png) | ![Image](image20.png) |
| H6   | ![Image](image21.png) | ![Image](image22.png) | ![Image](image23.png) | ![Image](image24.png) |
Figure 3: Segmentation results obtained by Modified Monkey Search Algorithm for high grade tumors
The selected MRI brain images of various patients affected with high-grade tumors form BRATS repository with the ground truth are used to assess the efficiency of the proposed MMS techniques. Because of complex tissue structure and distinguished boundaries, manual segmentation is difficult to locate the tumor region present in the MR brain slices. Especially for the MR brain slices with serial numbers H2, H4, H7, H8, H9, H11, and H12 with complex
tumor structures are efficiently segmented by the proposed MMS techniques. Multiple tumors present in the MR brain slices is also successfully segmented by the suggested modified monkey search algorithm

5. Comparison Parameters

5.1 Dice Overlap Index

The dice overlap measures the similar/correlated pixel of the ground truth image obtained from the BRATS dataset and segmented image delivered by the proposed techniques. The accuracy of segmentation can be measured by using the DOI values. Higher the DOI value produces better the segmentation results [13& 14].

\[
D(C, D) = 2 \times \frac{J(C,D)}{1+J(C,D)}
\]  

(4)

The proposed Modified Monkey Search (MMS) technique delivered an impressive DOI value as an average of 95.39 (%), which is quite better than the competitive techniques such as SOM, FCM, PSO-FCM and Cuckoo-IT2FCM. The quality of the proposed technique can be ensured with the higher DOI values [15]. The Figure.4 shows the accuracy of the proposed and conventional methods used for the segmentation process.

5.2 Computational time

The elapsed time is measured based on the time required for performing the demarcating of the tumor region present in the MR brain slices. The average time (1.194 seconds) is required for performing the demarcating of tumor portion located in the input MR brain image [17& 18].
Figure 5 shows the elapsed time of proposed and competitive segmentation techniques. Some of the segmentation techniques produce better segmentation results, but the time required for performing the segmentation will take a little bit more for the completion. The proposed MMS identifies the tumors with distinguished boundaries in various MRI sequences of images and all the segmentation task is performed in a short period time is another merit of using the proposed MMS technique [20 & 21].

5.3 Sensitivity
The accurate identification of tumor present in the input slices is measured using the sensitivity parameters [23 & 24]. The calculation of sensitivity value is performed using the following equation:

\[ OF = \frac{TP}{TP + FN} \]  

(5)

In the above equation, TP (True positive) – represents the accurate discrimination of tumor and other portion, FN (False Negative) – represents the unidentified tumor portion located in the MR brain slices [18].
The exact discrimination of tumor and other region is exactly measured using the parameters of sensitivity is displayed in fig 6. The Proposed MMS technique delivers improved sensitivity value of (99.12 %), which is better than the BAT-IT2FCM, PSO-FCM and FCM. Almost in all the input MR brain slices, the tumor regions are accurately located/discriminated by the proposed MMS algorithm [25 & 26].

6. Conclusion

The proposed modified monkey search (MMS) techniques less time for completing the demarcation process of all sequences of MR brain image also produces impressive dice overlap index (DOI) values, which is better than the conventional methodologies such as FCM, PSO-FCM and Cuckoo-IT2FCM. The high grade and low-grade tumors present in the input MR brain slices is effectively segmented using the suggested MMS techniques. The suggested techniques provide feasible solutions for the problem in terms of finding the tumors with complex structures and also with distinguished boundaries are successfully segmented. The suggested technique can act as better diagnostic tools for solving the impediment that arises during the diagnosis process of tumors in the MR brain image.

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