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Application of Firefly Algorithm in Automatic Extraction of Brain Tumor from Multi-Modality Magnetic Resonance Images

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Abstract

In this paper, an automated method for identifying the overall range of the tumor and extracting the starting point of brain tumors in Magnetic Resonance Imaging is presented. In this study, images of patients with glioblastoma multi-former were used. By first combining the features of the four MRI modalities, annoying areas such as the eyes, skull, and cerebrospinal fluid that may be problematic are removed. Brain tumors are highly bright in T1-Post images and dark in T1 images. Therefore, calculating the difference between these two images improves the resolution of the tumor area. After performing preprocessing and increasing the resolution of the tumor area, the enclosed frame (BB) algorithm is used. This algorithm is an automatic and fast segmentation method that determines the location of the tumor and its approximate size. After finding the presence of the tumor, the firefly algorithm is used to find the initial point of the tumor. By defining the objective function of moving fireflies to a point that has the maximum light intensity, we can find the point where the probability of a tumor is high. Next, using the growth of the tumor area, the entire tumor area can be extracted. The results show the appropriate speed and accuracy of the proposed method.

Keywords: Brain tumor, Images intensify regionally, Tumor growth, Enclosed box algorithm, Lightning worm algorithm
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1. Introduction

When most normal cells are old or damaged, they die and are replaced by new cells [1,2]. Sometimes, this process goes wrong; New cells form when the body does not need them, and old or damaged cells do not die normally. The production of extra cells often forms a mass of tissue, which is called an overgrowth or tumor [3,4].

Brain tumors are the most common cause of death due to neurological causes after stroke [5,6]. Although brain tumors are not relatively common, they have a high mortality rate. More than 50% of brain tumors are made up of brain gliomas. The most common brain glioma is glioblastoma multi-former (GBM), which is the most malignant brain tumor [7,8].

Recently, magnetic resonance imaging (MRI) has been widely used for high-resolution imaging of tissues, which is non-invasive in nature and has fewer risks [9,10]. Detection and segmentation of brain tumors on MRI images is very important in diagnosing diseases because it provides useful information about anatomical structures as well as abnormal brain tissues [11,12]. MRI images of the brain are used to diagnose tumors, one of the oldest of which is manual diagnosis by a specialist [13,14]. Unfortunately, this method is hard work and its performance is reduced by human errors. Therefore, automatic and semi-automatic methods for processing these images have been replaced. The semi-automatic method is a combination of manual and automatic methods. This method is more desirable than manual detection method due to its integrated knowledge of the problem, but it is also inefficient due to time consuming and the need for user interaction. In automated methods, tumor detection is achieved without user intervention and has created an interesting topic for researchers. Although automated methods may remove some of the limitations of semi-automated designs, some other factors may also impede their performance. The main challenges that limit the performance of automated methods are: variation in shape, position, tissue type and tumor size, etc. [15,16].

Several methods have been proposed to solve the problems of automatic detection. In some papers, general and local thresholding methods have been used to diagnose brain tumors on MRI images. Although these designs are simple, fast, and executable, they are unfortunately unable to accurately capture lesions because the background objects have the same intensity distribution as the tumors and their resulting histograms. This method uses only the histogram brightness information in the image, so it does not include the spatial information of the image [17,18].

In [19], the threshold-based segmentation method using the set of levels (TLS) has been used. TLS uses an algorithm to find the appropriate threshold value. First, the threshold value is specified by the user in the tumor area, and then the TLS algorithm provides a range of thresholds based on the initial value, and the greater the difference between the tumor area and the background, the wider the range. TLS does not require explicit knowledge of tumor functions and non-tumor density; it can be performed in an automated or semi-automated form depending on the complexity of the tumor shape. The algorithm presented to the MRI images of the head for tumor segmentation has been tested and its function has been visually and quantitatively evaluated. However, the need to manually select the desired area is a drawback for this method. In general, threshold segmentation methods are not able to extract all the data related to MRI images and are usually used as the first step in the segmentation process.

Other segmentation methods include the area growth method, which is used to extract similar interconnected pixels in an image [20,21]. In general, the area growth method is usually suitable for drawing simple and small structures such as tumors and wounds. In 2017, Sampong et al. Used the reference area growth method [22]. In this method, a number of pixels that were included in the tumor area are first identified. These pixels are then compared with the pixels of the adjacent area, and if they have favourable conditions in terms of tumor area growth, they are marked to be added to the desired area after the end of the process. To add pixels to the target area, you can use the methods to calculate the average brightness or compare the maximum brightness.

Image segmentation by clustering methods is one of the common methods in the field of image processing. Reference [23] presents a hybrid clustering system based on three main stages of pre-processing, clustering and extraction and contouring. The image obtained from the pre-processing stage is clustered by a medium K clustering process integrated with the fuzzy C medium algorithm and then extracted from the tumor region by the thresholding method. In the last step, the alignment level algorithm is applied to the image and provides a more accurate segmentation. Dependence of the output on parameters such as number of clusters, maximum iteration and termination parameter are the disadvantages of this method.

In some papers, neural networks have been used to segment brain tumors [24]. The main motivation for using the neural network is its similarity to the neural network of the human brain and the ability to intelligently extract the answer from the input, so that the necessary conditions for extracting the output are extracted from the input data. Neural networks use both light and spatial information to segment MRI images of the human brain and require trained data, so they are semi-automated; Because the trained data must be defined by the user for them [25]. In 2016, C used the multilayer perceptron neural network (MLP) to segment brain tumors. In this method, image noise is first removed in the pre-processing stage and lighting levels are standardized. Appropriate features are then extracted from the images and these features are applied to the neural network for training and testing. The performance of the proposed method is compared with the K-mean algorithm, the proposed method performs better than the K-mean algorithm both qualitatively and quantitatively [26]. In this method, collecting training data is not easy and the training phase is slow.

In a number of papers, the diagnosis is usually made in such a way that algorithms based on evolutionary processes are used to diagnose the tumor [27]. For example, the Particle Swarm Optimization (PSO) algorithm was developed in 1995 by Kennedy and Eberhart [28]. This method uses direct matching of information for search operations, which is inspired by the social behavior of birds. PSO is an optimization tool that is randomly assigned and seeks to find the optimal point by updating generations [29,30].

This algorithm does not have any complex evolutionary operators such as composition and mutation [31,32]. Laishram et al. used an automated method for tumor diagnosis and segmentation [33]. First, by pre-processing, the annoying areas such as the skull and background tissue are removed, and then the images are removed with the help of noise filter. Finally, by applying the PSO algorithm, the tumor is revealed in the images. In this method, images with T2 are used as input and have achieved an average accuracy of over 95%. Brain tumor segmentation methods have been proposed by different researchers and different results have been obtained so far. However, studies show that most existing algorithms are not yet fast enough and flexible enough, especially for clinical needs because in general, brain tumors may appear in any size, shape and location. This diversity has made the detection process difficult.

This paper proposes a new automatic and fast method. By combining the features of the four MRI imaging modalities, the pre-processing process is performed first and the annoying areas such as the skull, eyes and CSF are removed. Then, using the enclosed frame (BB) algorithm, an overview of the tumor location is found, in other words, the position of the tumor and its approximate size are determined. This algorithm speeds up the tumor detection process. The firefly algorithm is then used to find the initial point of the tumor. The algorithm is nature-inspired, and fireflies move to the point where they have the maximum light intensity. Then, using the growth of the tumor area, the entire tumor area is extracted. The structure of the paper is as follows. Therefore, expressing the subject and importance of research in the first part, in the second part, materials and methods are presented. The simulation and analysis results are shown and discussed in the third section. Finally, in the fourth section, the conclusion of the article is stated.

2. The proposed method

Twelve patients, including ten men and two women with contrast-enhanced region (CE) in their brain tumors, were selected as the primary data for this study (Henry Ford Hospital, Detroit, Michigan, USA). People are in the age range of 36 to 66 years with an average of 53 years [34]. The characteristics of these patients are given in Table 1.

Table.1.
Profile of 12 patients studied in this study

Patient	Age	Necrosis area	Man	Female
1	52	No	×	
2	36	No	×	
3	57	Within the CE area	×	
4	60	Within the CE area	×	
5	66	Within the CE area		×
6	47	Two zones, one within the CE zone	×	
7	46	No	×	
8	55	No	×	
9	62	Within the CE area	×	
10	62	Within the CE area	×	
11	41	Two zones, both within the CE zone		×
12	58	Within the CE area	×	

A) Pre-processing steps:

The pre-processing process, which involves removing the skull and eyes and cerebrospinal fluid, is as follows:

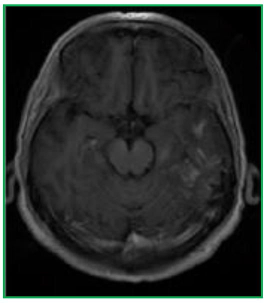
a) Removal of the skull: There are different algorithms for skull removal. In the BET method developed by Smith, the brain mask is first extracted from the image histogram by means of two estimated thresholds. Then, with the growth of the sphere in the center of gravity of the brain towards the edges of the brain, the whole area of the brain is determined. Sphere growth is controlled by two parameters of smoothness and local light intensity, thus removing the skull [35].

b) Removing the eyes: The eyes, which appear in the lower slice, have a high brightness in the images, which makes it difficult to detect the tumor. To remove them using histogram features (mean and scatter) from T1, T1-Post and FLAIR images, a suitable threshold is selected and areas with brightness intensities above this threshold are removed [36,37].

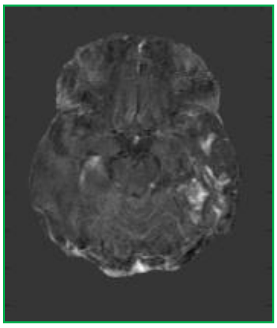
c) Removal of cerebrospinal fluid: CSF and ventricles also cause problems in detecting the tumor area. These areas in the image with light weight T2 and in the image with weight FLAIR darker than the threshold are extracted using the histogram features in the image with weight T2 and the areas darker than the threshold in the image FLAIR can be identified and from the images Deleted [38]. Fig. (1-a) shows the image of the brain before pre-processing and Fig. (1-b) shows the image of the brain after pre-processing. As can be seen, the annoying areas have been properly removed after pre-processing, and the tumor areas are quite clear.

B) Increasing the resolution of the tumor area:

In MRI-T1 post-contrast images, the tumor is light in color and in MRI-T1 image, the tumor is black. After removing the annoying areas, the resolution of the tumor area can be increased by obtaining the difference between T1 and T1-Post images. Fig. 2 shows the increased resolution of the tumor area.

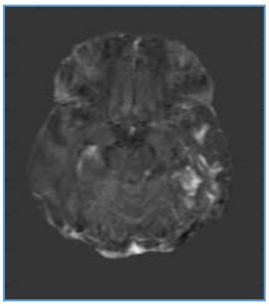


(a) Before preprocessing

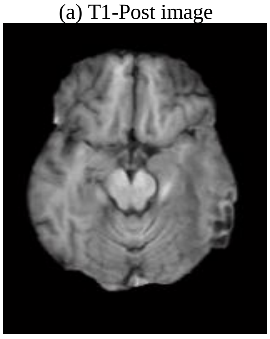


(b) After preprocessing

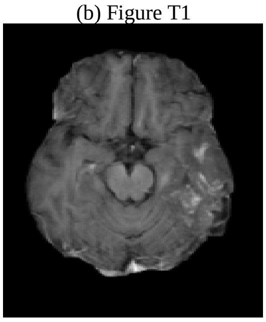
Fig. 1. Overview of the brain before and after preprocessing



(a) T1-Post image



(b) Figure T1



(c) The resulting image of the difference between the two images T1-Post and T1

Fig. 2. Increasing the resolution of the tumor area

C) Determining the total area of the tumor using the BB algorithm:

In this algorithm, it is assumed that the healthy human brain is inherently symmetrical left and right, and the geometric axis from the middle of the skull is considered as the axis of symmetry. When a tumor appears, the hemispheres of the brain become asymmetric. With this algorithm, the process of tumor diagnosis is performed quickly. In BB algorithm, the image is divided into two parts. If there is symmetry, the two parts of the brain will be the same, but if there is no symmetry, it means that there is a tumor in one part of the brain.

The changes are considered regional and the histogram of the regions is obtained and the difference of the histograms is calculated and a criterion is obtained. Based on this criterion, the presence or absence of a tumor can be detected. In this algorithm, the main image is divided into experimental (I) and reference (R) images. In BB, after finding the axis of symmetry, the left (or right) half is considered as the experimental image I, and the right (or left) half as the reference image R.

Here, the region of change D is limited to a rectangle whose purpose is necessarily to limit and identify anomalies. Here, the tumor or swelling is thought of as the "change" area in the test image, and all intracranial tissues except the tumor or swelling are treated as the "no change" area. In this research, a new scoring function is used that can determine the area of change D with two very fast searches, one in the vertical direction of the image and the other in the horizontal direction.

Fig. 3 shows the notations in which I and R show the test and reference images, respectively, having the same height h and the same width w. The rectangular area shows the relationship of the sub-area of change to the area of interest (tumor or swelling we are looking for) between images I and R.

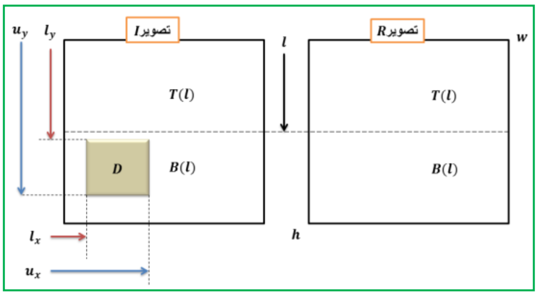


Fig. 3. Find D using experimental and reference images

When two normalized histograms are the same, the BC is the same between them, and when the two normalized histograms are completely dissimilar, the corresponding BC value is zero. Therefore, by comparing the similarity of histograms, it is possible to determine the area in which the tumor is likely to be present [39,40].

D) Firefly algorithm:

Firefly Algorithm is a nature-inspired multi-model meta-heuristic algorithm based on the glowing behavior of fireflies. The glow worm uses the glare of light as a signal to attract other glow worms [41,42]. In this algorithm, three main rules are considered, which are expressed as follows:

a) Every light worm, regardless of its gender, is attracted to other light worms because they are bisexual.

b) Relatively, according to the intensity of their illumination and vice versa in proportion to their search spaces, they are attracted to each other. Attracts.

c) If the firefly is not brighter around the worms, they move randomly.

Initially, based on the objective function, all objects (ghosts) will be randomly distributed throughout the search space. Light intensity is related to the target values. A firefly with a light intensity of more or less will absorb another special light cream with a light intensity of more or less. The charm of the firewall will be proportional to the intensity of the light obtained by the adjacent light worm.

E) Tumor growth:

For the growth of the tumor area at each stage, the pixels that are adjacent to the environment of the tumor area must be examined. The brightness of the pixels that are added to the tumor area should be very similar to the tumor area and differ from other areas. Therefore, for each pixel, the following two conditions must be considered:

$$f(x,y) - \mu_t^T \langle k \times std_t^T \quad (1)$$

$$f(x,y) - \mu_b^T \langle k \times std_b^T \quad (2)$$

where f (x, y) light intensity of the studied pixels, µb and stdt are the mean and scatter of light intensity of the tumor area µb and stdb are the mean and scatter of the non-tumor area in the T stage, respectively. If these two conditions are met, pixels will be added to the tumor area. This continues until no new pixels are added to the tumor area. In this way, the entire tumor area can be selected.

3. Simulation and analysis

According to the implementation of equivalent methods and techniques in BB algorithms and fireflies and tumor area growth and processing, the results of processing output for the diagnosis of brain tumors are expressed as follows:

A) BB simulation results:

In the BB algorithm, the overall view of the tumor ranges and position shown in Fig. 4 is first determined. Using the expressed relations and the BC coefficient in the BB algorithm, the image is divided into two regions. The changes are considered regionally and the histograms of the regions are obtained. The difference of histograms is calculated and a criterion is obtained. Based on this criterion, the tumor area in the brain can be identified, which has been done in previous studies with an error rate and low processing speed.

B) Simulation results of firefly algorithm:

After finding the range of tumor presence, the firefly algorithm is used to find the initial point of the tumor. Fig. 5 shows that 10 fireflies are randomly distributed in the image, then the fireflies move to places with higher light intensities.

The brightness of the tumor is high, so the target function is set to brightness, according to Fig. 6, the initial point of the tumor is obtained.

C) Simulation results of tumor area growth:

Then, after determining the initial point of the tumor, this area should be grown and the entire tumor area should be extracted. The growth of the desired region is based on the properties of adjacent pixels, and if the properties of neighboring pixels are close to the properties of the desired region, that pixel is added to the desired region to obtain the entire tumor region according to Fig. 7.

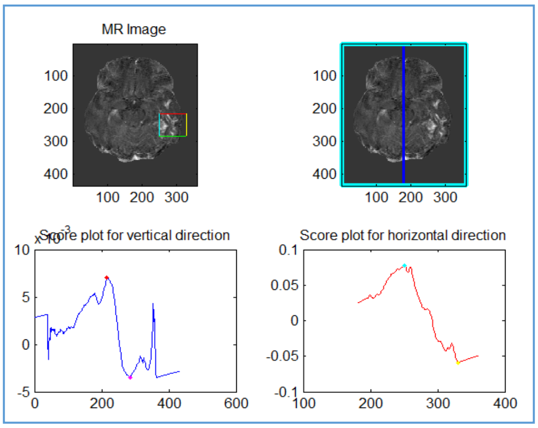


Fig. 4. BB simulation results

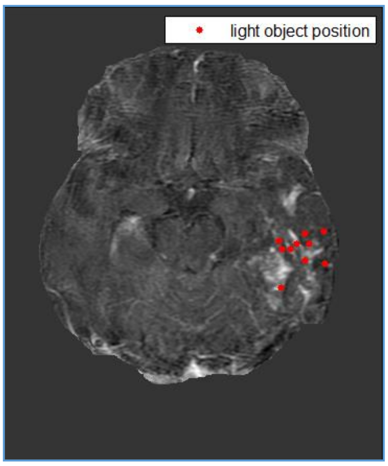


Fig. 5. Propagation of light worms in the presence of tumor

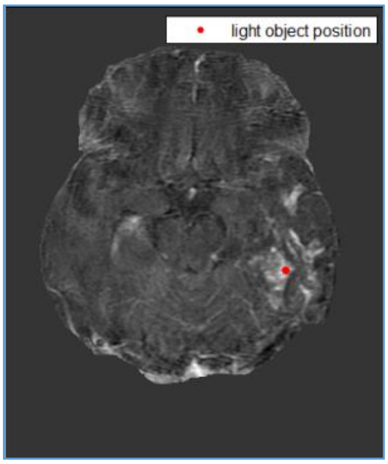


Fig. 6. The starting point of the tumor site

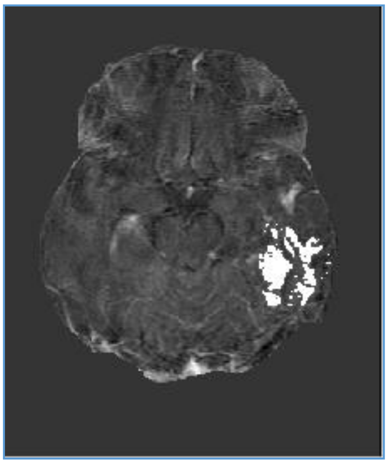


Fig. 7. Extraction of the tumor area by growth of the tumor area

4. Conclusion

In this article, a new method for tumor diagnosis was presented in which MRI images of twelve patients with glioblastoma were used to diagnose the exact location and dimensions of the tumor. In the first stage, preprocessing operations were performed on the images, which combined the modalities and removed the disturbing areas and improved the clarity of the tumor area. Then, BB algorithm was used to obtain the total tumor range. After finding the range of tumor presence, the firefly algorithm was used to find the initial point of the tumor and then the obtained starting point was grown until the entire tumor area was obtained.

The above processes are a new method in the field of automatic detection of brain tumors, which is the simultaneous use of all MRI imaging modalities, combination of modalities, use of firefly algorithm and tumor area detection are its innovative aspects. This method is very fast and reliable and can be used as a tool for clinical research. In addition, it reduces user interaction and operation time. In order to evaluate the efficiency of the method and its accuracy, the tumor range extracted in this method has been compared with the tumor range extracted manually by a skilled radiologist. The classification results obtained from the proposed approach in comparison with the radiologist's diagnosis are shown in Fig. 8, the correlation of about 99% indicates that the performance of the proposed method was appropriate.

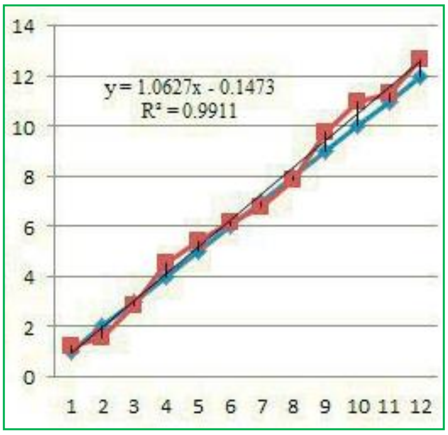


Fig. 8. Correlation diagram between the proposed method and the results of radiologist diagnosis (R2 = 9911)

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