



Detection of Brain Tumor using several segmentation methods

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Abstract : Segmentation of an image is an essential step and the most hypercritical task of image investigation. Its role is to extract tumors or remove tumors from an image of an image segmentation. Themechanization of medical image segmentation has recognized wide application in diverse areas. Segmentation is a mainly significant stage for analyzing images correctly and it affects the correctness. On the other hand, appropriate segmentation is hard because of the huge variety of lesion sizes, shapes, and colors along with diverse skin types and textures. In addition, some lesions have asymmetrical limits, and in a few cases, there is a flat transition between the lesion and the skin. Numerous algorithms have been planned to deal with this difficulty. In this paper, various algorithms are used to detect tumor-like Canny Algorithms, Otsu algorithm, Particle swam optimization Algorithm, and watershed Algorithm.

IndexTerms - MRI image, Textures of Image, Segmentation Algorithm.

1. Segmentation

Segmentation of an image is the primary step of image synthesis. The mechanization of medical image segmentation has constituted extensive application in variousareas such as decision for patients, conducting management planning, and computer-integrated surgery. Following are the segmentation algorithms that have been implemented.

1.1 Canny Algorithm

Canny edge detection is a technique to extract useful structural information from differentvision objects and intensely decrease the sum of data to be processed. It is applied in various computer vision systems. Canny has found that the requirementsfor the application of edge detection on varied vision systems are comparatively similar.

The Process of the Canny edge detection algorithm can be broken down to 5 different steps:

- Apply a Gaussian filter to smooth the image to remove the noise
- Find the intensity gradients of the image
- Apply non-maximum suppression to get rid of spurious responses to edge detection
- Apply double threshold to determine potential edges
- Track edge by hysteresis: Finalize the detection of edges by suppressing all theother edges that are weak and not connected to strong edges[1][2].

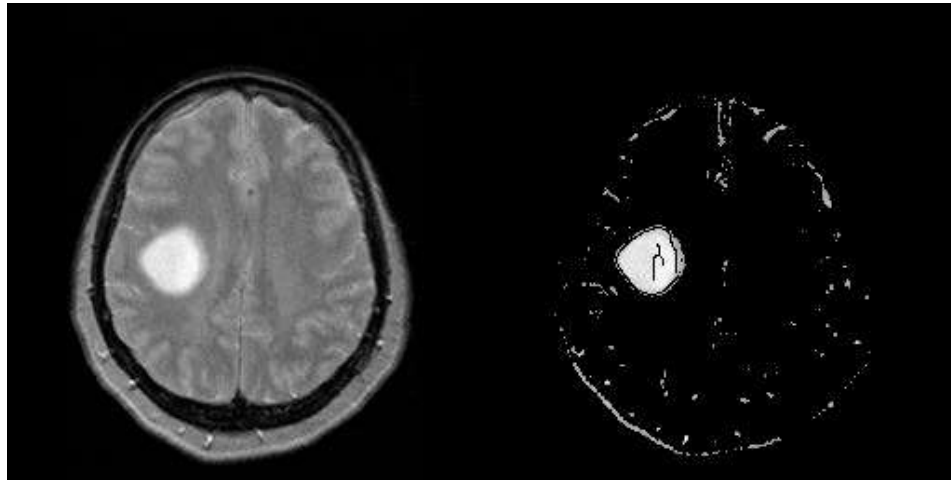


Figure 1: Output from Canny Algorithm

1.2 Otsu Algorithm:

In image processing, Otsu's method, named after Nobuyuki Otsu, is used to automatically perform clustering-based image thresholding, or, the reduction of a gray level image to a binary image. The algorithm assumes that the image contains two classes of pixels following bi-modal histogram (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their combined spread (intra- class variance) is minimal, or equivalently (because the sum of pairwise squared distances is constant), so that their inter-class variance is maximal[2]. The algorithm proceeds as follows:

- Compute histogram and probabilities of each intensity level
- Set up initial class probabilities and mean.
- Step through all possible thresholds $t = 1, 2, \dots, \text{maximum intensity}$
 Update class probabilities and mean
 Compute inter class variance
- Desired threshold corresponds to the maximum inter class variance[3].

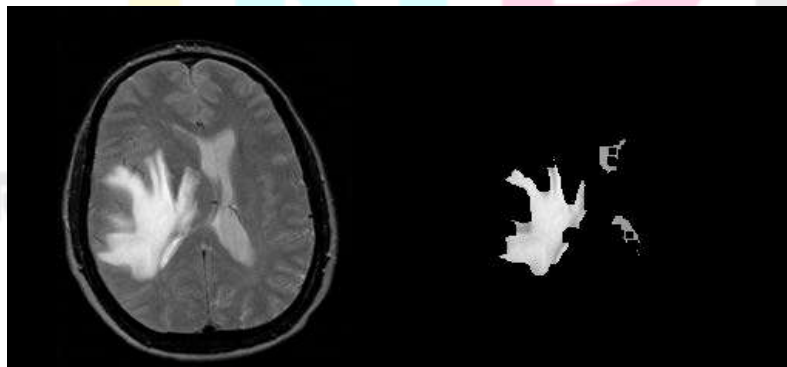


Figure 2: Output from Otsu Algorithm

1.3 Watershed Algorithm

Any grayscale image can be viewed as a topographic surface where high intensity denotes peaks and hills while low intensity denotes valleys. We start filling every isolated valley (local minima) with diverse colored water (labels). As the water rises, depending on the peaks (gradients) nearby, water from different valleys, obviously with different colors will start to merge. To avoid that, we build barriers in the locations where water merges. We continue the work of filling water and constructing barriers until all the peaks are under water. Then the barriers shaped gives the segmentation result[4].

But this approach gives over-segmented result due to noise or any other irregularities in the image. Hence, we have implemented a marker-based watershed algorithm where you specify which are all valley points are to be merged and which are not. It is an interactive image segmentation. Label the region which we are sure of being the foreground or object with one color (or intensity), label the region which we are sure of being background or non-object with another color and finally the region which we are not sure of anything, label it with 0. That is the marker. Then we apply watershed algorithm. Then our marker will be updated with the labels we give, and boundaries of objects will have a value of -1[5].

Marker-controlled watershed segmentation follows this basic procedure:

- Compute a segmentation function.
- Compute foreground markers.
- Compute background markers.
- Modify the segmentation function so that it only has minima at the foreground and background marker locations.
- Compute the watershed transform of the modified segmentation function.

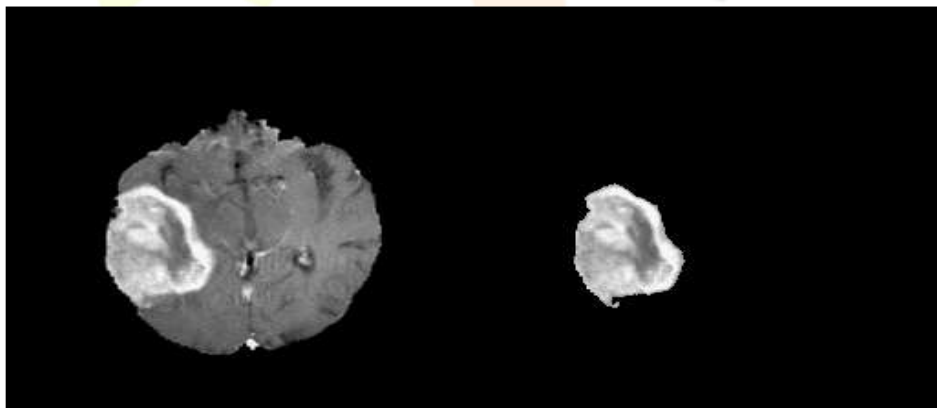


Figure 3: Output from Watershed Algorithm (Malignant)

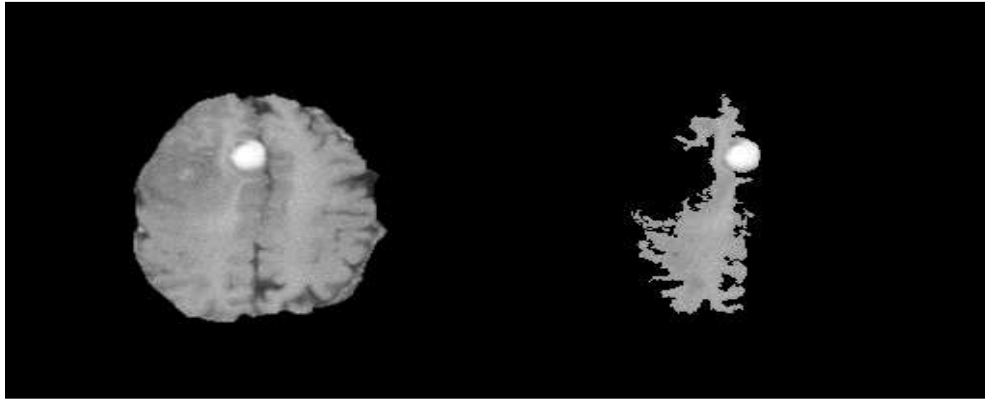


Figure 4: Output from Canny Algorithm (Benign)

1.3.1 Particle Swarm Optimization (PSO)

The PSO algorithm starts by generating random positions for the particles, within an initialization region $\Theta' \subseteq \Theta$. Velocities are usually initialized within Θ' but they can also be initialized to zero or to small random values to prevent particles from leaving the search space during the first iterations[6]. During the main loop of the algorithm, the velocities and positions of the particles are iteratively updated until a stopping criterion is met[7]. The update rules are:

$$v_i^{t+1} = wv_i^t + \varphi_1 U_1^t (b_i^t - x_i^t) + \varphi_2 U_2^t (l_i^t - x_i^t),$$

$$x_i^{t+1} = x_i^t + v_i^{t+1},$$

where w is a parameter called inertia weight, φ_1 and φ_2 are two parameters called acceleration coefficients, U_1^t and U_2^t are two $n \times n$ diagonal matrices in which the entries in the main diagonal are random numbers uniformly distributed in the interval $[0,1]$. At each iteration, these matrices are regenerated. Usually, vector l_i^t , referred to as the neighborhood best, is the best position ever found by any particle in the neighborhood of particle p_i , that is, $f(l_i^t) \leq f(b_j^t) \forall p_j \in N_i$. If the values of w , φ_1 and φ_2 are properly chosen, it is guaranteed that the particles' velocities do not grow to infinity[4].

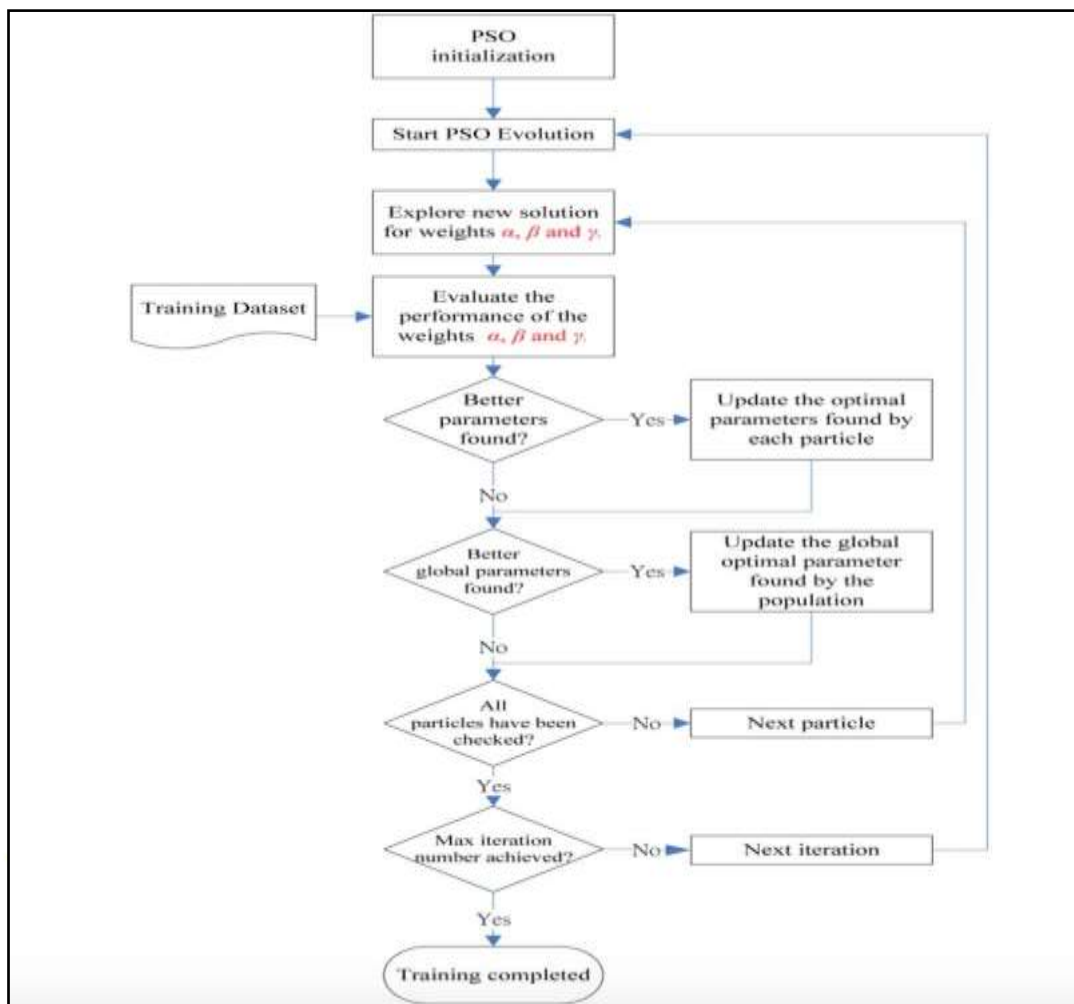


Figure 5: PSO Algorithm Flow Chart

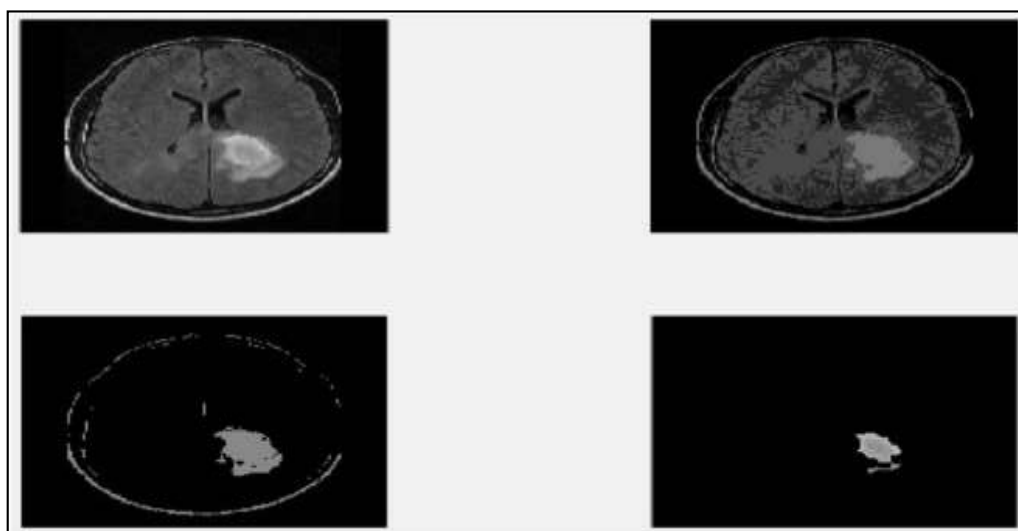


Figure 6: Output from PSO Algorithm (Malignant)

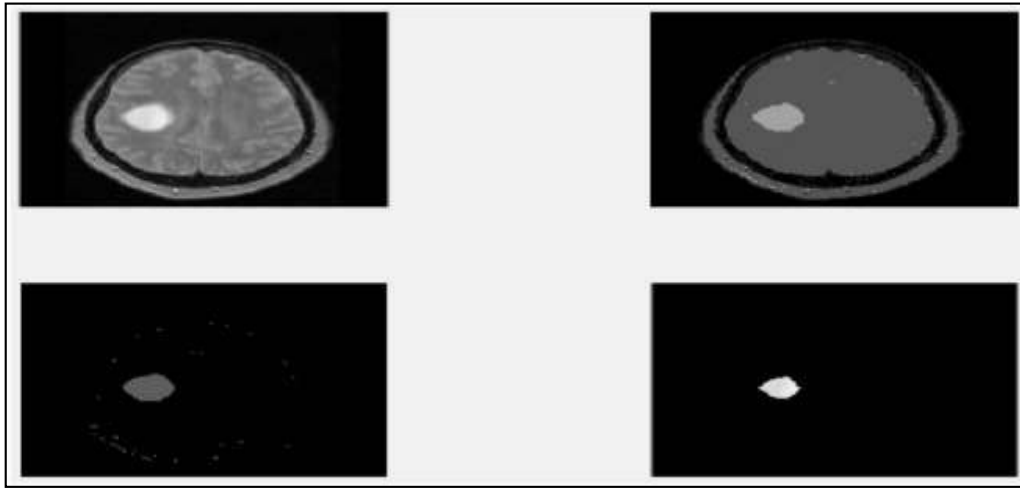


Figure 7: Output from PSO Algorithm (Benign)

Conclusion: Various segmentation methodologies are explored in the paper. For segmentation four segmentation algorithms are applied on the images such as Canny Method, Otsu's Method, Watershed algorithm and Particle Swarm Optimization algorithm. To segment tumor from the image It can be concluded that the algorithms and the parameters used in the proposed paper are all meant to increase the efficiency of the segmentation detection by achieving better results.

The boundary approach and the edge-based approach for segmentation are very common but the region growing approach gives better results. It is found that the particle swarm optimization algorithm gives the most accurately segmented tumors.

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