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OPTIMIZED BRAIN IMAGE THRESHOLDING USNG BFOA

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ABSTRACT

This paper introduces a novel optimal multilevel thresholding algorithm for brain magnetic resonance image segmentation. The optimization algorithm, applied for image histogram-based thresholding, is based on a relatively recent evolutionary approach known as bacterial foraging. Originally proposed towards the end of the last millennium, bacterial foraging is emerging as a strong contender for distributed control and optimization. The utility of the proposed method is demonstrated by considering several benchmark brain MRI images. The performance of the proposed algorithm, henceforth called BFOR, is compared with another contemporary, popular artificial life-based approach introduced for solving complex stochastic optimization problems, namely particle swarm optimization with linearly varying inertia weight PSW. The results obtained for the benchmark images were quite encouraging as BFOR comprehensively outperformed PSW.

Keywords: Brain MRI, Multilevel Thresholding, Image segmentation, Histogram, Bacterial Foraging, Particle Swarm Optimization

1. INTRODUCTION

Image segmentation is recognized as a crucial part (usually considered as almost a mandatory preprocessing step) of image analysis [1-3]. Segmentation partitions an image into its constituent parts. This basic operation helps to analyze and interpret a certain region of interest of an image [2,3]. It has numerous applications ranging from computer vision to target matching for defense applications. Another important field of application is medical science. For example, image segmentation aids in diagnosing abnormalities in the brain or any part of the body from MRI or PET scans. Currently, MRI is the most popular clinical diagnostic procedure for detecting brain disorders, as it is a completely non-invasive method. Moreover, its ability to produce high-resolution spatial images and its sensitivity towards differentiating neurological tissues assist in diagnosis, prognosis, pre-surgical and post-surgical treatment planning for various diseases, e.g., multiple sclerosis, schizophrenia, epilepsy, Parkinson’s disease, Alzheimer’s disease, cerebral atrophy, presence of any lesion like glioma, etc. If image segmentation can be done effectively, then the lesions, or the disorder, if present, can be classified to an effective micro-level.

Histogram-based thresholding is commonly known as a very popular tool for image segmentation. Here, the objective is to determine an accurate threshold (for bi-level thresholding) or multiple thresholds (for multilevel thresholding), so that the image can be subdivided into several levels for easier analysis and interpretation. Bi-level thresholding is the simplest problem, where in the histogram of the image grabbed, only one single valley is found, and accordingly, the voxels are grouped into two classes: one group of voxels with image intensity above the threshold and another below the threshold. Multilevel thresholding problems are more complicated, and the corresponding image segmentation problem can be configured as a multi-class classification problem where, based on the determined thresholds, voxels having a particular characteristic within a specified range are grouped into one class. Usually, it is not simple to determine the exact location of distinct valleys in a multimodal histogram of an image that can segment the image efficiently, and hence the problem of multilevel thresholding is regarded as a more challenging task.

Over the years, many researchers have proposed several algorithms for bi-level and multilevel thresholding of image histograms [4-15,30,31]. The main objective of many such schemes is to achieve optimal thresholding, such that the thresholded classes achieve some desired characteristic. Many of these methods attempt to achieve optimization of an objective function by, e.g., maximizing posterior entropy that indicates homogeneity of segmented classes [4,6,8,13,14], maximizing some measure of separability [5], employing index of fuzziness and fuzzy similarity measure [9,10,12], minimizing Bayesian error [30,31], etc. So far as brain MRI images are concerned, different segmentation techniques are widely being used [16-27], many of them being very similar to those above-mentioned methodologies. In this particular application domain, a 3-D reconstruction method of the brain from anisotropic MRI brain data has been proposed in [16].

The scheme encompasses an automatic segmentation technique that includes gray level thresholding of white and gray matter, a global white matter segmentation with 3-D connectivity, and gray matter segmentation with local 3-D connectivity. In [17], segmentation and thresholding, augmented by a stochastic relaxation method, have been proposed for detecting small lesions like multiple sclerosis from 3-D brain data. A spectral graph theoretic method, namely, normalized cut (NCut) with Nystrom approximation, based on local 3-D histograms of brightness, has been selected for segmenting vertebral bodies from sagittal T1-weighted MR images in [18]. In [19], a hybrid model consisting of a radial basis network and active contour model for multispectral brain MRI segmentation has been presented. Often the quality of segmentation methods, for performing tissue classification, gets hampered by multiple imaging artifacts such as noise and intensity inhomogeneities [20]. To alleviate these problems, the authors in [20] presented an image processing method, first using multi-resolution wavelet transform for high-quality image denoising and then using a fuzzy segmentation method to segment the image, which has shown some success in medical segmentation. In the work, fuzzy restrained histogram FCM clustering segmentation method is used, which is characterized by good partitioning property and strong robustness. A triangulation of the surface of the head and brain was obtained by using the minimum distance method [20]. In [21], MR brain image has been processed using Hidden Markov Models based on 3-D image segmentation.

In [22], the proposed algorithm has been demonstrated to be capable enough to handle multidimensional classification problems. The work in [22] presents a general framework to integrate a new type of constraints, based on spatial relations, in deformable models. In the proposed approach, spatial relations are represented as fuzzy subsets of the image space and incorporated in the deformable model as a new external force. Three methods to construct an external force, from a fuzzy set representing a spatial relation, are introduced. This framework is then used to segment brain subcortical structures in magnetic resonance images (MRI). A training step is proposed to estimate the main parameters defining the relations. The results demonstrate that the introduction of spatial relations in a deformable model can substantially improve the segmentation of structures with low contrast and ill-defined boundaries.

In [23], segmentation of brain MRI is achieved by applying non-parametric density estimation employing the mean shift algorithm in the joint spatial-range domain. The concept of edge confidence map and adjacency graph is introduced to detect the class boundaries. For each structure, a maximum a posteriori probability criterion has been applied, both for real and synthetic data. The combined process of region segmentation and edge detection emerged to be a robust technique as sufficient clusters are automatically recognized despite noise and bias. Yu et al. [25] have proposed a fuzzy c-means based algorithm for bias estimation and segmentation of brain MRI. A complete automatic 3-D segmentation algorithm for brain MR scans is proposed in [26] that employs Bayesian estimation technique. In [26], a new hybrid technique for fully automated segmentation of brain MRI has been proposed. The hybrid strategy combines an elastic template matching approach followed by a stochastic heuristic (an evolutionary approach) to control the behavior of the template of deformable shape of a target structure.

Our present paper proposes the development of a novel optimal multilevel thresholding algorithm, especially suitable for multimodal image histograms, for segmentation of T2 weighted brain MRI, employing bacterial foraging technique. Bacterial foraging is comparatively a very recent method that is being used for solving multidimensional global optimization problems [28]. In foraging theory, it is assumed that the objective of the animals is to search for and obtain nutrients in such a fashion that the energy intake per unit time is maximized [28]. This foraging strategy has been formulated as an optimization problem by employing optimal foraging theory. The foraging behavior of E. coli bacteria present in our guts, which includes the methods of locating, handling, and ingesting food, has been successfully mimicked to propose a new evolutionary optimization algorithm [28,29]. The performance of the proposed algorithm, henceforth called BFOR, is extensively evaluated and compared with another artificial life-based evolutionary algorithm for multidimensional stochastic optimization, particle swarm optimization with linearly varying inertia weight [32,33], henceforth called PSW. The performance evaluation is carried out on the basis of several benchmark 256 x 256 MR brain images. The results show that the proposed BFOR based algorithm can significantly outperform the PSO-IW based algorithm, on the basis of both the performance indices considered in this paper: maximization of the fitness function as well as maximizing the uniformity factor, a popular measure employed to quantitatively determine the efficiency of the image segmentation algorithm [34].

The rest of the paper is organized as follows. Section 2 presents an overview of bacterial foraging technique followed by the proposed bacterial foraging based algorithm for multilevel thresholding. Section 3 presents the entropy criterion based measure employed for optimal thresholding. Performance evaluation is presented in detail in Section 4. Conclusions are presented in Section 5.

Bacterial foraging technique

Natural selection tries to extinct animals with poor "foraging strategies". Foraging strategies are basic means of survival techniques that include locating, handling, and ingesting food. This elimination process entails the propagation of genes of those animals, which have triumphant foraging strategies, as they are more likely to enjoy reproductive success. After generations, poor foraging strategies take much better shape and can be called that poor foraging gets redesigned. A foraging animal maximizes its energy obtained per unit time spent in foraging given the constraints of its own physiology and environment [28,29]. This evolutionary process of foraging has led researchers to conceive it as an optimization tool. An example of foraging behavior is shown by E. Coli bacteria present in human guts. The control system of these bacteria describes the foraging behavior, which can be subdivided into four actions, namely, chemotaxis, swarming, reproduction, and elimination or dispersal.

Chemo taxes

These motion patterns are the responses bacteria exhibit in the presence of chemical attractants and repellents, achieved through swimming and tumbling movements facilitated by their flagella. An E. coli bacterium alternates between two modes throughout its lifetime: running (swimming for a certain period) and tumbling. During a tumble, a unit-length random direction, denoted as $\gamma(j)$, is generated to determine the bacterium's direction of movement after the tumble. This stochastic movement pattern enables the bacterium to navigate its environment effectively in search of nutrients or to avoid harmful substances.

In particular

$$\varphi^{i}(j+1,k,l) = \varphi^{i}(j,k,l) + C(i)\gamma(j) \qquad (1)$$

where $\varphi^{i}(j,k,l)$ represent the i^{th} bacterium j^{th} chemo tactic k^{th} reproductive and l th elimination and dispersal step, $C(i)$ is the simple chemo tactic step size taken in the random direction specified by the tumble.

Swarming

When a group of E. coli cells is placed at the center of a semisolid agar containing a single nutrient, they disperse outward in a ring-like pattern. This movement occurs as the cells navigate up the nutrient gradient formed by the nutrient's consumption. If a high concentration of a sensory substance is used as the nutrient, it triggers the release of an attractant, causing the bacteria to cluster. The cells then move with a high bacterial density in a concentric formation. This swarming behavior continues as the cells emit attraction signals to one another, facilitating coordinated movement and aggregation.

Reproduction

The less healthy bacteria, denoted as S_r, are eliminated, while the healthier bacteria reproduce by splitting into two. The offspring are placed at the same location as the parent, ensuring that the bacterial population remains constant throughout the process. This mechanism reflects the reproduction stage of the bacterial lifecycle and is integral to maintaining the algorithm's efficiency and stability.

$$S_r = \frac{S}{2} \qquad (2)$$

Elimination and dispersal

The algorithm monitors each bacterium, tracking whether they are in the correct position based on the nutrient gradient. If a bacterium is not in the optimal location, it is placed back into the "food space," effectively resetting its position. This process assists in the chemotaxis behavior, allowing the bacteria to begin their search for nutrients from the starting point again. This iterative approach helps optimize the solution by guiding the bacteria to more favorable positions over time.

Entropy based multilevel optimal thresholding

The popularly employed entropy criterion for satisfactory determination of optimal thresholds of image histograms, as utilized in segmentation problems, was proposed by Kapur et al. in [4]. The original algorithm was developed for bi-level thresholding and was later extended for multiple levels. The multilevel algorithm can be described as follows. Let there be L gray levels in a given image, in the discourse $\{0,1,2,\ldots,(L-1)\}$. Then, let us define $P_i = h(i)/N$ $(0 \le i \le (L-1))$ where $h(i)$ = number of pixels with gray level i and N = total number of pixels in the image = $\sum_{i=0}^{L-1} h(i)$.

Performance evaluation

To evaluate the performance of the proposed segmentation method when applied to magnetic resonance brain images, we have utilized several downloaded benchmark MR brain images, freely available from a web-based medical image repository. All the images considered for segmentation are axial, T2-weighted MRIs of several brain slices. Each

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image is of 256 x 256 size, and each of these gray images has 8-bit representations of their intensity levels. Hence, there are L=256 gray levels in each image and its corresponding histogram. We have applied our proposed method for several of these image slices and compared these results with the PSO algorithm employing linearly varying inertia weight (called PSW).

The input is selected from the database and is depicted in figure 1.

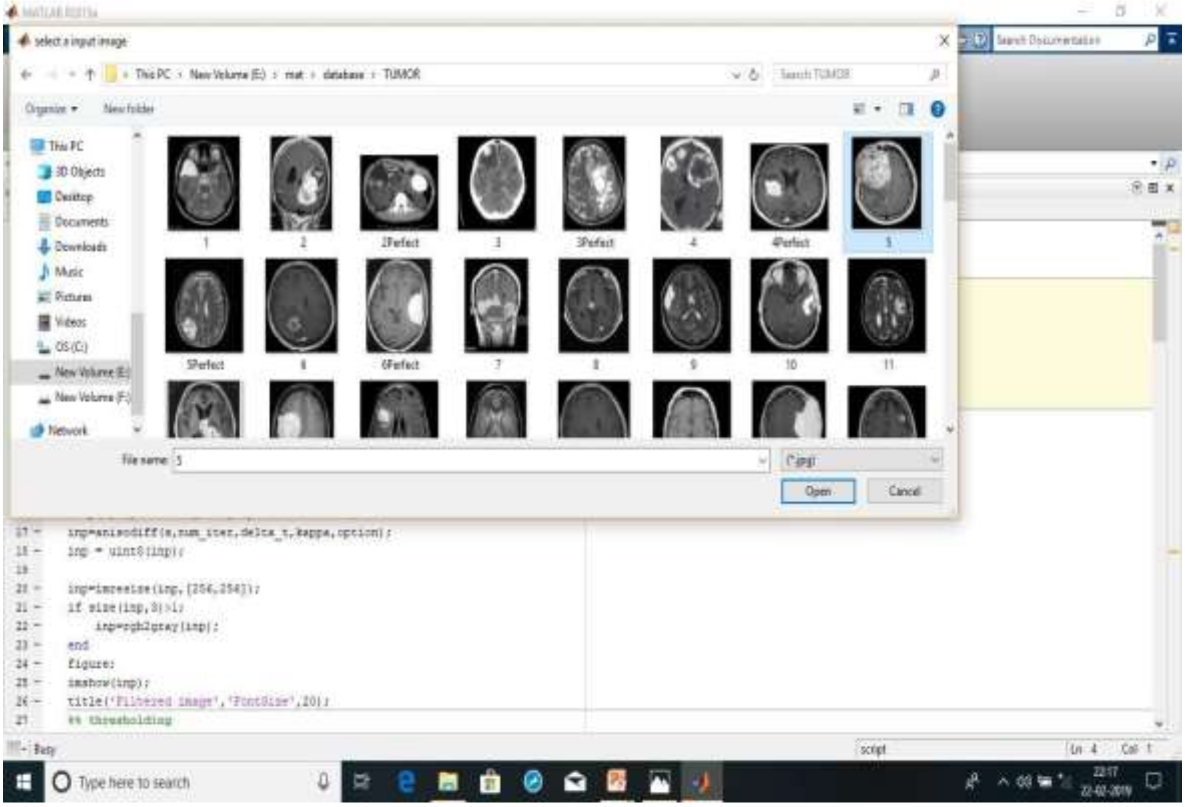
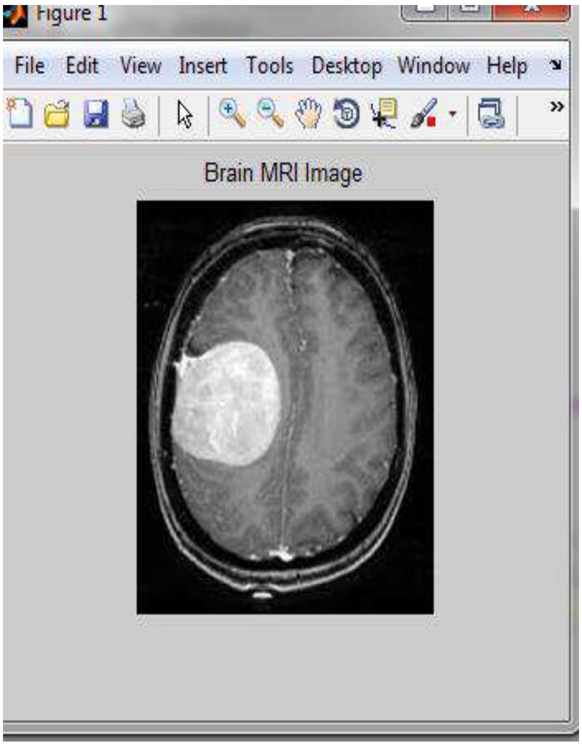


Figure 1 Select a input from database

The value of this uniformity measure, u, should be a positive fraction, i.e., it should lie between 0 and 1. A higher value of u indicates that there is better uniformity in the thresholded image, depicting better quality of thresholding. Conversely, a lower value of u indicates worse quality of the thresholding procedure.



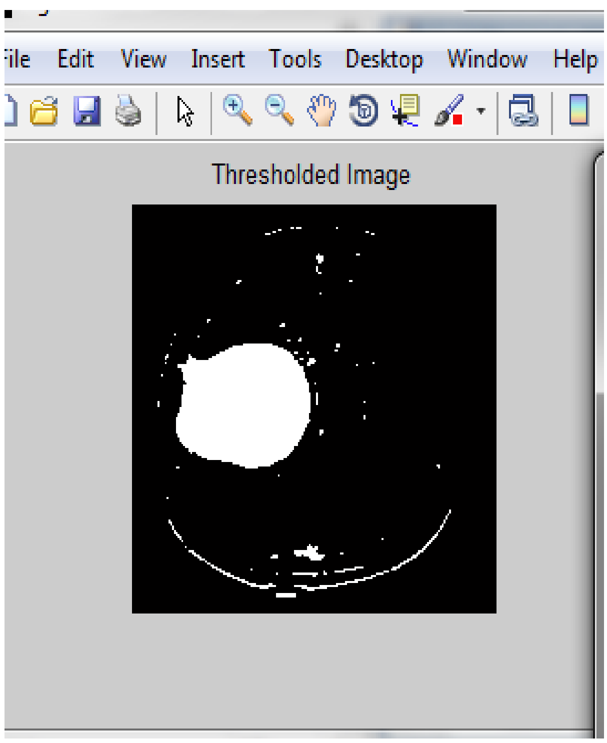


Figure 2 Input MRI image

Figure 3 Thresholded image

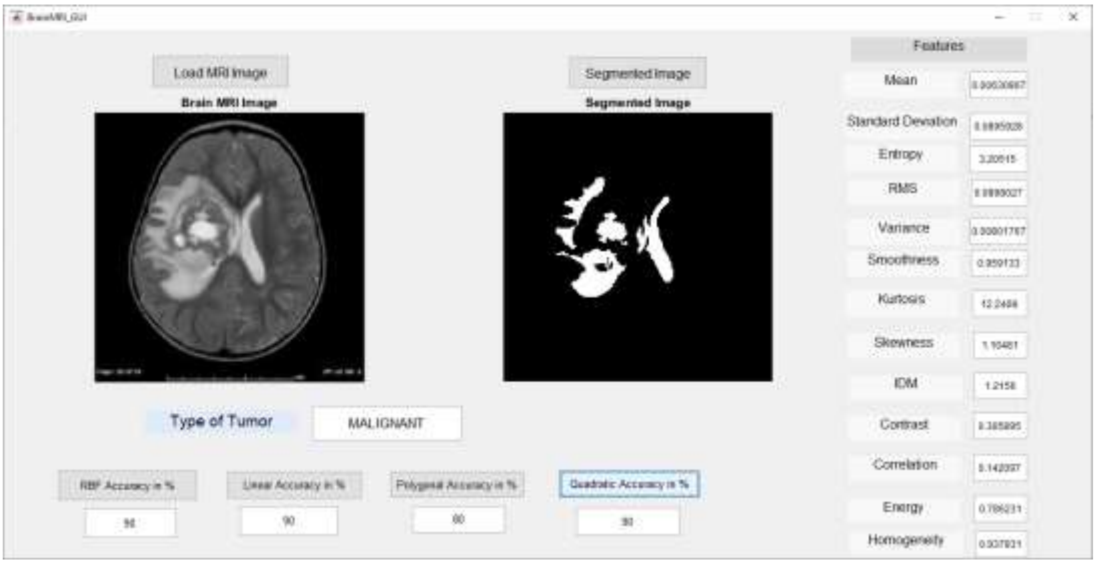


Figure 4 Detection of malignant tumour in threshold images

The input MRI image is shown in the figure 2 and its corresponding thresholded image is created as shown in the figure 3. The detection of malignant tumour among the thresholded images is depicted in figure 4.

2. CONCLUSION

This paper presented an optimal multilevel thresholding algorithm utilizing the bacterial foraging technique. Inspired by the evolutionary behavior of E. coli bacteria, the algorithm follows four key locomotory steps: chemotaxis, swarming, reproduction, and elimination/dispersal. Through these processes, E. coli bacteria navigate toward nutrient-rich regions, optimizing their foraging strategy. By emulating this survival mechanism, an optimization technique is developed that efficiently searches for and converges to the global optimum. The proposed algorithm, BFOR, is evaluated against another contemporary artificial life-based stochastic global optimization method, PSW. Segmentation results on benchmark MR brain images demonstrate that BFOR significantly outperforms PSW in terms of both objective function maximization and uniformity measure.

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