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Amended bacterial foraging algorithm for multilevel thresholding of magnetic resonance brain images

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ABSTRACT

Magnetic Resonance (MR) brain image segmentation into several tissue classes is of significant interest to visualize and quantify individual anatomical structures. Traditionally, the segmentation is performed manually in a clinical environment that is operator dependant, difficult to reproduce and computationally expensive. To overcome these drawbacks, this paper proposes a new heuristic optimization algorithm, amended bacterial foraging (ABF) algorithm for multilevel thresholding of MR brain images. The optimal thresholds are found by maximizing Kapur's (entropy criterion) and Otsu's (between-class variance) thresholding functions using ABF algorithm. The proposed method is evaluated on 10 axial, T_2 weighted MR brain image slices and compared with other evolutionary algorithms such as bacterial foraging (BF), particle swarm optimization (PSO) algorithm and genetic algorithm (GA). From the experimental results, it is observed that the new method is computationally more efficient, prediction wise more accurate and shows faster convergence compared to BF, PSO and GA methods. Applying the proposed thresholding algorithm to these images can help for the best segmentation of gray matter, white matter and cerebrospinal fluid which offers the possibility of improved clinical decision making and diagnosis.

1. Introduction

Image segmentation is an indispensable preliminary process in the visualization of human tissues, particularly during clinical analysis of magnetic resonance images. Medical image segmentation is a complex and challenging task, due to the intrinsic nature of the images. The brain has a particularly complicated structure and its precise segmentation is very important for detecting tumors, edema and necrotic tissues, in order to prescribe appropriate therapy. Magnetic resonance imaging (MRI) is a valuable diagnostic imaging technique for the early detection of abnormal changes in the tissues and organs. It possesses good contrast resolution for different tissues and has advantages over computerized tomography (CT) for brain studies due to its superior contrast properties. Hence, majority of research in medical image segmentation concerns MR images [1–4].

Image thresholding is one of the most popular segmentation techniques due to its simplicity, robustness and accuracy [5–8]. It is based on the assumption that the objects can be distinguished by their gray levels. In the case of bi-model (two classes) thresholding, the optimal threshold is the one that permits to separate different objects from each other or different objects from the background. The automatic fitting of this threshold is one of the main challenges of image thresholding. Over these years, many methods have been proposed for bi-model thresholding [9–12]. In particular, Kapur's [11] and Otsu's [12] methods are the two popular methods commonly employed in thresholding techniques.

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Kapur [11] finds optimal thresholds by maximizing the entropy of the histogram of gray levels for the resulting classes. In Otsu's method [12], the objective function is defined using between-class variance of the pixel intensities. The above methods are very efficient in case of bi-model thresholding. However, they are computationally expensive extending to multilevel thresholding since they exhaustively search the optimal thresholds to optimize the objective functions. To overcome this drawback, many methods have been proposed for multilevel thresholding [13–18]. In these methods, the objective is to determine accurate multiple thresholds (for multilevel thresholding), so that the image can be subdivided into several levels for their easier analysis and interpretation.

Reddi et al. [13] proposed a fast search scheme for finding single and multiple thresholds that maximize the interclass variance between dark and bright regions. Papamarkos and Gatos [14] have specified the multi-threshold values as the global minima of the rational functions which approximate the histogram segments by using hill clustering technique to determine the peak locations of image histogram. Yin and Chen [15] proposed a fast iterative scheme for multilevel thresholding methods. In this method, the multilevel thresholding problem is divided into consecutive bi-level thresholding problems, and then the value of each threshold is adjusted to optimize the corresponding objective. The process is iterated until no threshold is able to move. However, the results would tend to local optima when the number of thresholds is more than three.

Lim and Lee [16] proposed a method which smoothes the gray-level histogram by the Gaussian convolution. Tsai [17] presented a fast thresholding selection procedure for multimodal and unimodal histograms. In [17], Gaussian kernel smoothing and local maximum curvature methods are used to detect peaks and valleys in a multimodal histogram, and points of discontinuity in a unimodal histogram. Lio et al. [18] showed that the recursive algorithm greatly reduces the computational complexity of the multilevel threshold determination by accessing a look-up table when compared with conventional Otsu and Kapur methods. But it still suffers from the problem of long durated processing time when the number of thresholds m increases.

Different segmentation techniques are widely being used for MR brain images. Clustering is the most popular method for medical image segmentation, with fuzzy c-means (FCM) clustering and expectation–maximization (EM) algorithms being the typical methods, the applications of the EM algorithm to brain image segmentation is reported in [19,20]. A common disadvantage of EM algorithms is that the intensity distribution of brain images is modeled as a normal distribution, which is not the fact for noisy images.

The FCM algorithm has also been employed in many researches [21,22]. Historically, FCM clustering algorithm introduced by Bezdek is based on minimizing an objective function, with respect to the fuzzy membership and set of cluster centroids [23]. It has the drawback of increase in sensitivity of the membership function to noise. If MR image contains noise or is affected by artifacts, their presence can change the pixel intensities, which will result in an improper segmentation. To eliminate such problems, Tolas and Panas post processed the membership function to smooth the effect of noise [24]. Dave proposed the noise cluster (NC) to deal with noisy clustering data in the approach [25]. However, it is not suitable for image segmentation, since noisy pixels should not be separated by other pixels.

Pham presented a new approach of FCM, and named as the robust fuzzy c-means (RFCM) algorithm [26]. Ahmed et al. introduced the other improved versions of FCM by the modifications of the objective functions [27]. All these methods inevitably introduce computation issues, by modifying most equations along with the modification of the objective function. Shan et al. presented the automated histogram-based brain segmentation in T_1 weighted 3D MR brain images [28]. A complete fully automatic 3D segmentation using hybrid geometric-statistical model is presented for brain images [29]. The hybrid strategy combines an elastic template matching approach followed by a stochastic heuristic approach to control the behavior of the deformable shape template for a target structure. Moreover, it has the drawback of slow rate for convergence. Ma et al. [30] proposed a review on the current segmentation algorithms used for medical images. The algorithms are classified according to the principal methodologies based on thresholds, clustering techniques and the deformable models.

Evolutionary algorithms, also known as general-purpose optimization algorithms, are capable of finding near-optimal solutions to the numerical, real-valued test problems whereas exact analytical methods do not produce the optimal solutions quickly. In image segmentation, evolutionary techniques are applied to find the optimal threshold values with less computation time [31–37]. One of the evolutionary algorithms which have been introduced by Passino [38] recently is bacterial foraging algorithm. In this scheme, the foraging (methods for locating, handling and ingesting food) behavior of *Escherichia coli* bacteria present in our intestines is mimicked. It was successfully used to solve various engineering problems such as harmonic estimation [39], transmission loss reduction [40], active power filter for load compensation [41], power network [42], load forecasting [43], independent component analysis [44] and antenna array optimization [45].

In this paper, an amended bacterial foraging (ABF) algorithm for solving the multilevel thresholding in image segmentation is proposed. The proposed method considers two objective functions of the Kapur's and Otsu's methods. The feasibility of the proposed method is tested on 10 benchmarked T_2 weighted MR brain images and compared with BF, PSO and GA methods. It has been shown that the ABF technique offers superior performance in terms of solution quality and convergence speed than the BF, PSO and the GA.

The paper is organized as follows: Section 2 formulates the multilevel thresholding problem. The overview of bacterial foraging (BF) algorithm is described in Section 3.