Multi-level medical image thresholding based on metaheuristics: A comparative Study

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1 Introduction

Image thresholding is the most used technique to extract objects from the background of an image. It is widely used because of its simplicity and effectiveness for real time image segmentation. A variety of thresholding classification is given in the literature. But most of the authors classify the thresholding methods in two classes: parametric and non parametric methods. According to the segmentation technique, this problem is either combinatorial or continuous optimization, consequently many optimization techniques were used to solve it as metaheuristics. Indeed, metaheuristic techniques have been extensively used to search the optimal thresholds for parametric and non-parametric approaches in the case of multilevel thresholding . In this paper, a comparative study of the use of metaheuristic techniques for multilevel medical image thresholding problem is presented.

We present, in what follows, some researches using Simulated Annealing (SA), Gemetic Algorithms (GA) and Particle Swarm Optimization(PSO)meta-heuristics in the field of medical image thresholding techniques.

2 Single solution based metaheuristics

The most used single solution based metaheuristic is Simulated Annealing (SA) many works solved the segmentation problem using SA as in [3]. A new variant of Simulated Annealing, called Enhanced Simulated Annealing (ESA), adapted to continuous problems was developed by Nakib and al. [3] . The authors proposed the use of a multi-objective optimization approach to find the optimal image segmentation thresholds of two criteria: (1) the within-class criterion and (2) the overall probability of error criterion. The improved SA was used for solving the histogram Gaussian curve fitting problem and optimizing the image segmentation multi-objective criterion. The proposed segmentation method, called Combination of Segmentation Objectives (CSO), has the advantage of being non-supervised [3]. Thereby, to calculate the initial number of the regions in the image, an iterative algorithm which detects the significant peaks of the histogram was developed. The number of the detected peaks corresponds to the number of regions in the image. The coordinates of these peaks are then the initial values of the histogram Gaussian curve fitting procedure. After that, to compute the within-class criterion, the histogram of the image is fitted to a sum of Gaussian curves thanks to the proposed ESA. For the second criterion, that is the overall probability of error criterion, the homogeneity is calculated for each image pixel. Finally, the thresholding process is applied by optimizing the multi-objective function. In . [1] the authors proposed an automatic multilevel thresholding technique involving the optimization of the two-dimensional (2D) exponential entropy based on hybrid micro-canonical annealing for microscopic images. The 2D maximum exponential entropy has the advantage of considering the distribution of the gray-level information and the spatial information by using the 2D-histogram. But, the problem with this method is its time consuming computation. To overcome this problem, the authors propose to hybridize the Microcanonical annealing (MA) with Nelder-Mead (NM) simplex method [2] which was proved to be very efficient for non convex and combinatorial optimization. The developed optimization algorithm, named NM-MA, has been tested on microscopic images.

The experimental results, obtained by CSO, were compared with the classical Otsu method [4] and the method using the Gaussian curve fitting only (GCF) [5]. The experiments conducted on unimodal and bimodal images showed that the proposed method is more efficient than the classical Otsu method and the method based on the Gaussian curve fitting only [3].

3 Population based metaheuristics

An MRI image segmentation method based on two-dimensional survival exponential entropy (2DSEE) and particle swarm optimization (PSO) was proposed in [12] . The 2DSEE technique considers the cumulative distribution of the gray level information, and it takes also advantage of the spatial information using the 2D-histogram. To overcome the problem of time-consuming computation of 2DSEE, the authors have proposed to use the optimization metaheuristic PSO. PSO was proved to be efficient for non convex continuous and combinatorial optimization. The experiments on segmentation of MRI images proved that the proposed method achieve a satisfactory segmentation with a low computation cost [12]. Indeed, the computation of the speed gain factor and the time values showed the effectiveness of the PSO and confirmed that the proposed method is fast compared to other methods such as the method developed by [13] or [14] where the result is obtained after more than 120s [14]. The MRI images were also tested with the classical 2D Shannon Entropy (2DSE) and it was shown from the experiments that the results provided by the method based on 2DSEE and PSO optimization are more homogeneous than those provided by 2DSE [12].

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