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Color image segmentation based on multiobjective artificial bee colony optimization

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ABSTRACT

This paper presents a new color image segmentation method based on a multiobjective optimization algorithm, named improved bee colony algorithm for multi-objective optimization (IBMO). Segmentation is posed as a clustering problem through grouping image features in this approach, which combines IBMO with seeded region growing (SRG). Since feature extraction has a crucial role for image segmentation, the presented method is firstly focused on this manner. The main features of an image: color, texture and gradient magnitudes are measured by using the local homogeneity, Gabor filter and color spaces. Then SRG utilizes the extracted feature vector to classify the pixels spatially. It starts running from centroid points called as seeds. IBMO determines the coordinates of the seed points and similarity difference of each region by optimizing a set of cluster validity indices simultaneously in order to improve the quality of segmentation. Finally, segmentation is completed by merging small and similar regions. The proposed method was applied on several natural images obtained from Berkeley segmentation database. The robustness of the proposed ideas was showed by comparison of hand-labeled and experimentally obtained segmentation results. Besides, it has been seen that the obtained segmentation results have better values than the ones obtained from fuzzy c-means which is one of the most popular methods used in image segmentation, non-dominated sorting genetic algorithm II which is a state-of-the-art algorithm, and non-dominated sorted PSO which is an adapted algorithm of PSO for multi-objective optimization.

1. Introduction

Image segmentation is an essential procedure used in low-level preprocessing. Moreover, it is the most important step to analyze images and to extract meaningful data for many applications of computer vision and pattern recognition. This operation partitions a digital image into distinct regions which consist of the pixels with similar attributes such as intensity, color and texture. Great varieties of segmentation techniques have been presented in literature. However, the obtaining segmentation with an exact accuracy is often a very challenging task, especially for natural images. The successes of segmentation algorithms widely depend on the concept of the region homogeneity represented by a similarity criterion and determining the distinctive features extracted from the image. Image segmentation techniques can be categorized into four general approaches: threshold-based, edge-based, region-based, and clustering-based methods [1].

The threshold-based methods assume that an image is composed of regions with different intensity ranges. The optimum threshold values are determined by the histogram of the image which has the valleys between two adjacent peaks. Owing to its simplicity, histogram thresholding is a widely used technique for monochrome image segmentation. But it is not a trivial job for color image because of its multi-dimensional structure [2,3]. The edge-based methods identify the boundaries of objects by applying an edge filter to the image. Unlike the edge-based segmentation which returns boundaries between regions, the region-based methods aim to determine the regions directly. In this technique, segmentation is regarded as spatial clustering. This means that every pixel must be a member of region and the pixels in a region are connected to each other by means of pixel neighborhood. These methods have two operations: merging and splitting. In the merging strategy also known as region growing, initially all pixels are assumed to be a distinct segment which should be merged according to a similarity criterion until no segments remain to be merged. In the splitting

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strategy, the entire image is assumed as a single segment which should be split until each region satisfies the homogeneity. Considering the segmentation process that aims to group the pixels in an image with respect to some similarity measures, it can basically be handled as a clustering problem. Determination of cluster validation is a widely studied issue. Many algorithms based on clustering such as fuzzy c-means, Expectation Maximization, and genetic algorithms have been used for image segmentation [4,5].

Recent efforts have demonstrated that the hybrid approaches based on swarm intelligence can be used as an effective tool in this field. Omran et al. [6] proposed a dynamic clustering approach based on particle swarm optimization for image segmentation and they tried to automatically determine optimum number of centroids. ACO-based region-growing approach was proposed by Ramos and Almeida [7]. Huang et al. [8] applied this model for partitioning medical images. Ma et al. [9] proposed a fast image segmentation method based on artificial bee colony algorithm to estimate the appropriate threshold values in a continuous grayscale interval. Cinsdikici and Aydın [10] proposed a hybrid approach of matched filter and ant colony optimization algorithm for extraction of blood vessels in ophthalmoscope images. Aydın and Ugur [11] presented a color clustering method based on ant colony optimization for the detection of flower boundaries. Akay [12] put forward the search abilities of PSO and ABC algorithms on multilevel thresholding. Sag and Cunkas [13] applied an ABC-based clustering algorithm to the image segmentation.

As a new trend, multi-objective optimization algorithms have been used in problem formulation for image segmentation. Multiobjective optimization also known as Pareto optimization is an extension of optimization with single objective. This methodology enables to optimize several conflicting objectives simultaneously and it has been successfully applied in several engineering problems such as electromagnetic absorbers design [14], definition of design variables and loading for I-beam [15], etc. The multiobjective optimization algorithms based on metaheuristic techniques are suitable method to deal with natural image segmentation problem which contains multiple objectives such as maximization of inter-region compactness and minimization of intra-region separation. Nakib et al. [16] used a multiobjective optimization algorithm based on the adapted NSGA2 to find the optimal thresholds for test images. On the other hand, Saha and Bandyopadhyay [17] presented a multiobjective clustering approach for MR brain image segmentation. Two cluster validity indices to be optimized were used in simulated annealing based strategy. Then Saha et al. [18] developed a multiobjective differential evolution based on FCM by using similar validity indices. They applied the algorithm to satellite images with the aim pixel classification. Bong and Rajeshwari [19] submitted a comprehensive review of the nature inspired multiobjective optimization techniques used in image segmentation. They have reported that a typical image segmentation procedure involves feature selection, pattern proximity, grouping and cluster validity analysis. Determination of the feature set plays the most decisive role in clustering. Mostly, only intensity values of pixels are insufficient. Multiple features should be extracted for image segmentation in which the regions to be found can involve edge, color and texture information. Withal, inter-pattern similarity which has conflicting objectives such as spatial coherence and feature homogeneity are related to multiple criteria. Considering the previous studies, clustering technique is generally used for pixel classification by ignoring spatial relationship.

Beside abovementioned categorization, color image segmentation has also been an attractive research topic in this field, which still protects its popularity, since color images have more distinctive features than grayscale images. The human eye can recognize thousands of color shades and intensities whereas only two dozen shades of gray are perceived. The objects which cannot be extracted only from intensity can easily be obtained by using color. In this paper, a new color image segmentation algorithm based on the seeded region growing and multiobjective optimization has been proposed. The segmentation is posed as a clustering problem through grouping image features in this approach. First, a feature vector that consists of seven members is constructed by composing color components, texture and homogeneity datum. Then homogeneous regions in an image are segmented by considering spatial coherence through the seeded region growing technique. On the other hand, cluster validation is ensured by IBMO with respect to compactness of inter-region and separation of intra-regions. IBMO is developed by authors in [20] that is a multiobjective extension of artificial bee colony optimization algorithm. IBMO is used here for automatic determination of both the optimal location of cluster centers and similarity threshold values between regions. In order to test the potential of the proposed algorithm, the segmentation results are compared with other three algorithms: non-dominated sorted PSO (NSPSO) [21], non-dominated sorting genetic algorithm 2 (NSGA2) [22] and fuzzy c-means (FCM) [23]. The comparative results of performance metrics show that the adapted version of IBMO is a promising method for color image segmentation.

The rest of the paper is organized as follows. The Section 2 focuses on the basic theory of multi-objective optimization; also ABC and IBMO algorithms are explained in details. Then the feature extraction techniques are described in Section 3. The proposed color image segmentation approach is presented in Section 4. The experimental results and evaluation metrics are explained in Section 5. Finally, a brief conclusion is presented in Section 6.

2. Methods

Image segmentation problems actually have multiple objectives such as minimizing overall deviation, maximizing connectivity, minimizing the features or minimizing the error rate of the classifier, etc. [24]. In this context, image segmentation problem can be handled as a multiobjective optimization problem (MOO). The multiple-objectives approaches used in literature can be categorized in two classes. These are weighted-sum method and Pareto-Optimal approaches. In the weighted sum approach, the best solution which corresponds to the minimum or maximum value of the problem is sought by combining all objectives into a function with a weighted formula. The first class converts a MOO problem into a single-objective problem. This type of optimization may be preferred as a useful tool in case of non-competing objectives. However, many real world optimization problems such as image segmentation contain more than one conflicting objectives to optimize simultaneously. Unlike the aggregating functions, Pareto-based methods enable the consideration of the dominances between objectives apart from obtaining a set of solutions. In this concept, a solution is called as Pareto Optimal or non-dominated solution that are superior to the rest of the solutions but inferior to other solutions in the search space when considering all objectives [25]. The general formulation of the problem can be defined as follows:

$$\begin{aligned} &\text{Maximize/Minimize} && y = f(x) = \{f_1(x), f_2(x), \ldots, f_M(x)\} \\ &\text{Subject to} && g(x) = \{g_1(x), g_2(x), \ldots, g_J(x)\} \le 0 \\ & && h(x) = \{h_1(x), h_2(x), \ldots, h_K(x)\} = 0 \\ &\text{where} && x = \{x_1, x_2, \ldots, x_N\} \in X \\ & && y = \{y_1, y_2, \ldots, y_N\} \in Y \end{aligned} \tag{1}$$

where x is set of the decision or feature vectors and X is the parameter space, y is the objective vector, Y is the objective space, $g(x)$ and $h(x)$ is the constraints imposed on the decision variables.