A Multi-objective Evolutionary Algorithm for Color Image Segmentation

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Abstract. In this paper, we present a multi-objective segmentation approach for color images. Three objectives, *overall deviation*, *edge value*, and *connectivity measure*, are optimized simultaneously using a multi-objective evolutionary algorithm (MOEA). To demonstrate the effectiveness of the proposed approach, experiments are conducted on benchmark images. The results justify that the proposed approach is able to partition color images in a number of segments consistent with human visual perception. For quantitative evaluation, we extend the existing *Probabilistic Rand Index* (PRI) considering multi-objective segmentation. The outcomes show that the proposed approach can obtain non-dominated and near-optimal segment solutions satisfying several criteria simultaneously. It can also find the correct number of segments automatically.

Keywords: Image segmentation · Multi-objective evolutionary optimization · Probabilistic Rand Index (PRI) · Color image · Pareto-front

1 Introduction

Images are considered one of the most important mediums of conveying information. Understanding images and extracting the information from them is an important aspect of many practical applications in various fields such as biology, medicine, remote sensing, chemistry, robotics, and industry. Image segmentation is one of the most significant and basic tasks in the field of image processing and recognition. The main goal of image segmentation is to partition an image into multiple non-intersecting regions (set of pixels) having high similarity among the pixels within a region, while the pixels among neighboring regions are significantly dissimilar with respect to some similarity measures. A large variety of different segmentation approaches have been proposed for monochrome and color images [2,3,5]. However, color image segmentation techniques are considered more appealing since they can provide more information than grey level

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images, and the human eye is able to better detect objects when color is available within the image [3].

Real-world image segmentation problems actually require considering multiple objectives, i.e., minimize overall deviation, minimize segment overlap, maximize connectivity, minimize the number of features, or minimize the error rate of the classifier. However, existing image segmentation approaches are generally concerned with a single objective [4,11]. By contrast, practical segmentation problems are multi-objective by nature and they require the decision makers to consider a number of criteria before arriving at any conclusion. A segmentation that is optimal with respect to a given criterion might be a poor candidate for some other criteria. Thus, a single solution that can optimize all objectives simultaneously does not necessarily exist. Hence, the trade-offs (Pareto-optimality) involved in considering several different criteria provide useful insights for the decision makers. Consequently, image segmentation falls into the category of multi-objective optimization problems.

To date, relatively few techniques have been developed for multi-objective image segmentation [9,13]. Most of these algorithms suffer from the "cluster number dependency" problem, where the user should provide an accurate number of clusters in advance [12]. However, in most practical situations, it is not known in advance. In addition, none of the proposed approaches considers the use of Pareto-optimality. The case is far worse in the case of color images, where there exists no approach for segmentation considering multiple objectives.

Unlike conventional methods that aggregate multiple objectives to form a composite scalar objective, multi-objective evolutionary algorithms (MOEAs) are capable of considering each objective separately and guiding the search to discover the global Pareto-optimal front. Motivated by this, in this paper, we propose a multi-objective segmentation approach for color images with the use of Pareto-front by simultaneous optimization of three objectives. The objectives, (*i*) overall deviation, (*ii*) edge value, and (*iii*) connectivity measure, are simultaneously optimized using the Strength Pareto Evolutionary Algorithm-2 (SPEA-2) [15]. Experiments on ten color images from the Berkeley Image Segmentation Dataset (BSDS300) [8] show that our proposed approach is able to partition natural and human scenes in meaningful objects. Experimental results also justify that our approach can find a set of non-dominated and near-optimal segmentation by simultaneous optimization of multiple objectives. This is particularly beneficial to decision makers, as they can select the best compromise solution according to specific segmentation objectives required in different cases.

We also present quantitative evaluation based on the well known concept of Probabilistic Rand Index (PRI) [14]. The original PRI was formulated for image segmentation based on a single objective, where the approach under consideration produces only one segmentation solution. Since we are using MOEA, instead of a single output image solution, we will find a set of Pareto-optimal segmentation solutions. Therefore, we modify the original PRI for handling a set of final solutions to produce the final PRI value. Based on this *Modified PRI*, we compare our approach with the algorithms proposed by Amelio and Pizzuti [1] (single objective and considers only the gray-level information), by Maji et al. [7] (single objective, but for color images), and by Amelio and Pizzuti [2] (single objective, but for color images). Comparison shows that the proposed approach gets better segmentation accuracy for most of the test images.

The rest of this paper is organized as follows. Section 2 explains the proposed approach. Section 3 describes the *Modified PRI* as the proposed quantitative evaluation criteria for color image segmentation. Section 4 provides the experimental results and discusses the findings. Section 5 concludes the paper with suggestions for future research.

2 Proposed Approach

Our approach can be summarized in the following steps: (*i*) representation of the input image, (*ii*) generation of a minimum spanning tree (MST) from this, (*iii*) initial segmentation from the MST, and (*iv*) utilizing the MOEA to optimize the objectives and to produce the final set of Pareto-optimal segmented images.

2.1 Representation of Individuals

The representation of individuals is a graph structure [13]. Figure 1 illustrates the genotype and phenotype for a 4×4 pixel image. In this figure, each number represents an index in the genotype which corresponds to the pixel index in the two-dimensional input image. The dotted sections in the phenotype indicate the segmentation. The length of a genotype is equal to the number of pixels of the input image. Each gene contains one out of five possible values; {*left*, *right*, *up*, *down*, *none*}; that describes how the graph node representing the input image pixel at the index of that gene is connected to its neighbors. Each graph node can connect to either one of its four cardinal neighbors, or to itself. If a graph node at an edge of the image plane points in an outwards direction, it is treated as having the value none. This means that all possible chromosome permutations are valid.

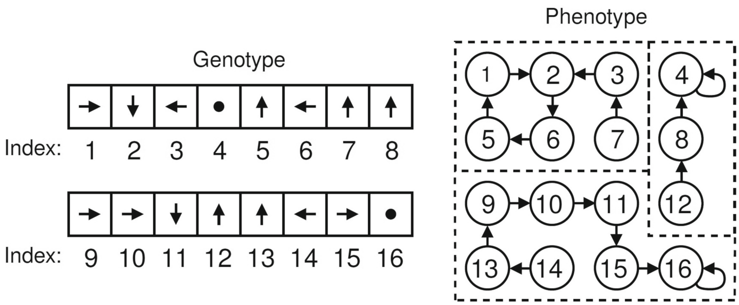


Fig. 1. Individual representation for a 4×4 pixels image.

Initial genotype sequences are generated by constructing a MST from the input image. This is to provide a good starting point for image segmentation. The input image is treated as a graph where each pixel is a node that is connected to each of its cardinal neighbors. The weight of each edge is given by the *Euclidean* distance in RGB color space between the two neighbors. From the initial image graph, we utilize Prim's algorithm [6] to generate a MST from a random starting point. Since a random starting point is used, a different MST is generated as the basis of the genotype for each initial individual.

2.2 Generation of Initial Segments

In order to evaluate an individual, the genotype is requited to be converted into the phenotype (initial segmentation). For this, the directions of edges in the graph described by the genotype is ignored. Starting with the first pixel node in the graph, all directly or indirectly connected pixel nodes are assigned to the same segment. This process is continued until all pixel nodes have been assigned to a segment.

2.3 Objective Functions

After creating the initial segmentation, three objectives are simultaneously optimized using the SPEA-2. The first objective, the *overall deviation*, is a measure of the similarity of pixels in the same segment, as defined in Eq. 1:

$$\text{overall-deviation}(C) = \sum_{C_k \in C} \sum_{i \in C_k} dist(i, \mu_k) \tag{1}$$

where C is the set of all segments, μ_k is the centroid of the pixels in the segment C_k, and $dist()$ is the distance function. Overall deviation should be minimized. Minimizing overall deviation roughly increases the number of segments. The distance function, $dist()$, is the *Euclidean* distance in the RGB color space, and is defined as:

$$\delta_{RGB} = \sqrt{\Delta R^2 + \Delta G^2 + \Delta B^2} \tag{2}$$

The second objective, the *edge value*, evaluates the overall summed distances on boundaries between the segments. This value is a measure of the difference in the boundary among the segments. This objective should be maximized. However, to keep similarity with other two objectives, we convert it as subject to minimization by negating it as shown in Eq. 3. Here, N is the number of pixels, F_i indicates the 4 nearest neighbors of pixel i.

$$\begin{gathered} Edge(C) = -\sum_{i=1}^{N} \left(\sum_{j \in F_i} x_{i,j} \right), \\ where, x_{c,s} = \begin{cases} dist(c,s) & if \nexists C_k : c, s \in C_k \\ 0, & \text{otherwise} \end{cases} \end{gathered} \tag{3}$$

The third objective, the *connectivity measure*, is defined in Eq. 4. This objective evaluates the degree to which neighboring pixels have been placed in the same segment, as follows:

$$Conn(C) = \sum_{i=1}^{N} \left(\sum_{j=1}^{L} x_{i,nn(j)} \right), \qquad where, x_{c,s} = \begin{cases} \frac{1}{j} & if \nexists C_k : c, s \in C_k \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

Here, N is the number of pixels in a segment, $nn(j)$ is the j-th nearest neighbour of the i-th pixel, L is a parameter determining the number of neighbors that contribute to the connectivity measure. In this work, we use $L = 8$. As an objective, the connectivity measure will also be minimized.

2.4 Evolutionary Operators

We use a tournament selection of size 4 in our experiments. Simple uniform crossover operator combines two randomly selected parent individuals to produce two child individuals. When applied, the mutation operator selects a random gene in a parent individual and sets it to a new value which is randomly selected from {*left*, *right*, *up*, *down*, *none*}.

3 Evaluation Criterion: *Modified PRI*

The Berkeley dataset contains multiple human-traced segmentation for each color image, all of those are considered equally reliable. Therefore, the comparison should be made against all the manually obtained ground-truth segmentations. For such comparison, *Probalistic Rand Index* (PRI) is introduced in [14] as an extension of *Rand Index* [10] which was designed to assess clustering methods. However, PRI is designed to evaluate the segmentation approaches those produce single final segmented solution only.

On the contrary, our aim to find a set of Pareto-optimal segmented outputs instead of a single output image by simultaneous optimization of three objectives. Therefore, we have modified the PRI into *Modified PRI* to asses multiple trade-off solutions. Given a set $\{GT_1, ..., GT_T\}$ of ground-truth segmentations of an image I consisting of n pixels, and a test set of Pareto-optimal segmentation results $\{I_1, ..., I_p\}$, the *Modified PRI* is defined as:

$$\begin{aligned} Modified\ PRI\ (\{I_1, ..., I_p\}, \{GT_1, ...GT_T\}) \\ = \frac{1}{H} \sum_{i \neq j} [c_{ij} p_{ij} + (1 - c_{ij})(1 - p_{ij})] \end{aligned} \tag{5}$$

where c_{ij} denotes the event that pixels i and j have the same label, p_{ij} is the probability, and $H = n \times (n - 1)/2$ is the total number of pixel pairs. Similar to the PRI, the *Modified PRI* values also varies between 0 and 1, where 0 means that $\{GT_1, ..., GT_T\}$ and $\{I_1, ..., I_p\}$ are completely dissimilar.

4 Experiments and Results

In this section, we present the results of our proposed approach on ten test images from the BSDS300 [8] and compare the performances in partitioning natural and human scenes in meaningful objects with the segmentations obtained by *C-GeNCut* [2], and *Biased NCut* [7] (referred as *C-NCut* hereafter) both for color images, and by *GeNCut* [1] that takes into account only gray-scale information, on the same images.

4.1 Experimental Setup

The parameters for the SPEA-2 are: population size = 50; generations = 100; archive size = 20; crossover probability = 0.7; mutation probability = 0.2. We use a constraint on initial segment size within the range of 1 to 50. In our experiments, five independent runs are made with each test image and the final Pareto-fronts from these runs are combined. Finally, a non-dominated sorting is performed to constitute the best non-dominated set of solutions.

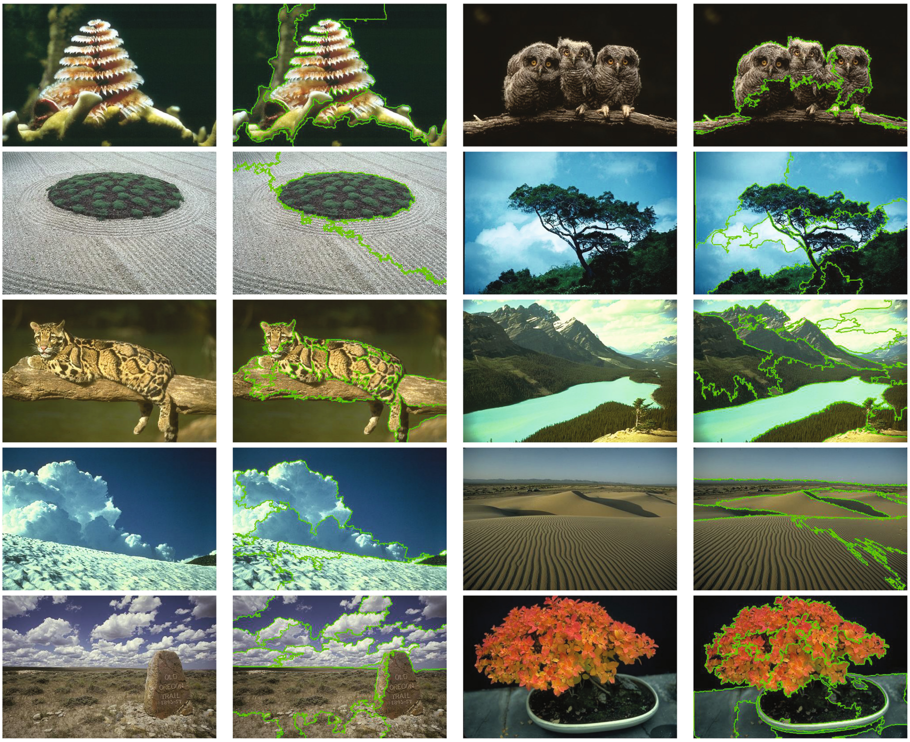
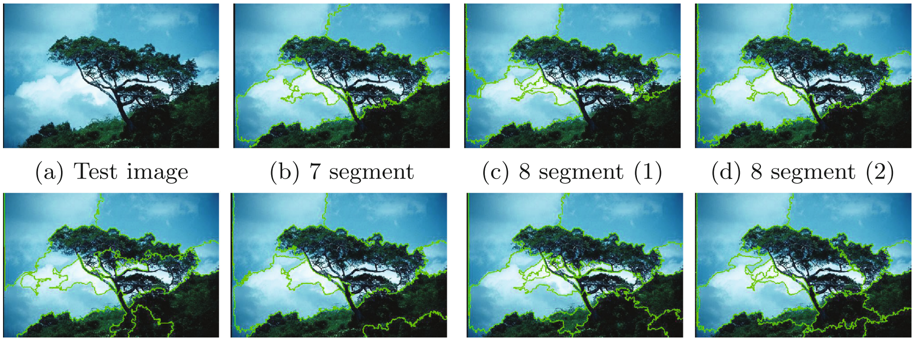


Fig. 2. Segmentation obtained by our proposed approach. For each image, the original version together with the segmentation results are presented.

4.2 Results and Discussion

Figure 2 presents the segmentation outputs produced by the proposed approach by depicting the contours of the regions on the original image. It is worthy to mention that each of these ten examples are one member of the final Pareto-optimal segmentation for each image. Each image of this figure is selected randomly from the corresponding Pareto-front. The figure also shows that the visual perception of the segmentation results is quite positive. For each test image, the main objects are identified as well as the segmentation process can successfully extract the most meaningful features.



(a) Test image (b) 7 segment (c) 8 segment (1) (d) 8 segment (2)

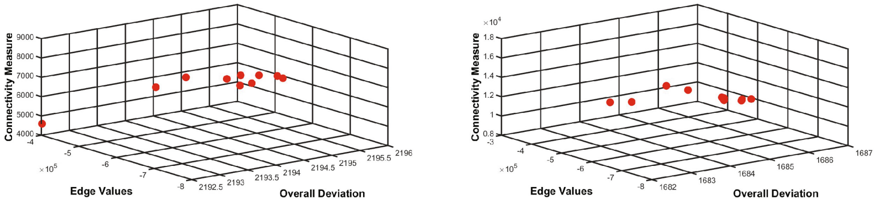
(e) 10 segment (f) 11 segment (g) 12 segment (h) 15 segment

Fig. 3. Examples of the image segmentation results for image index 147091 with number of segments.

Another objective of this work is to verify whether various trade-off segmentations are obtained. Figure 3 shows examples of the segmentation results for image index 147091. The results show that several trade-off segmentations with different numbers and shapes, all of which can be considered to be relatively good from visual perspective. This also shows that our proposed approach can find the optimal/near-optimal number of segments automatically.

This is also justified by Fig. 4 which shows the obtained Pareto-front by the proposed approach. From the figure, it can be found that our approach can successfully optimize the objectives simultaneously and the obtained solutions of each image have different Pareto-fronts. Although the shapes of the Pareto-fronts are different, a wide range of solutions is found in all cases. The diverse solutions, in particular the extreme solutions, are useful for real-world scenarios where the decision maker can select the best compromising segmented solutions from the non-dominated set of solutions according to the specific requirements or scenarios. All these ultimately justify the effectiveness of our proposed approach as a multi-objective image segmentation approach for color images.

Table 1 presents the quantitative comparison of our proposed approach with *C-GeNCut* [2], *C-NCut* [7], and *GeNCut* [1]. This table is partially taken from [2].



(a) 176039 (b) 178054

Fig. 4. Obtained Pareto solutions by the proposed method.

Table 1. Comparison based on *Modified PRI*

Image index	GeNCut	C-GeNCut	C-Ncut	Proposed Max	Approach Avg
I1 (12074)	0.7308 (0.0118)	**0.782** (0.0101)	0.7512 (0.0018)	0.7424	0.7206 (0.0138)
I2 (42044)	0.8036 (0.0186)	0.8288 (0.0379)	0.7565 (0.0001)	**0.8311**	0.7973 (0.0128)
I3 (86016)	0.6443 (0.0637)	0.7526 (0.0263)	0.7862 (0.0003)	**0.7946**	0.7766 (0.0157)
I4 (147091)	0.7041 (0.0183)	0.7052 (0.0183)	0.6651 (0.0017)	**0.7476**	0.7314 (0.0175)
I5 (160068)	0.8215 (0.0002)	**0.8361** (0.0163)	0.8217 (0.0001)	0.7475	0.7393 (0.02)
I6 (176035)	0.7797 (0.0375)	0.8361 (0.0075)	**0.8557** (0.0001)	0.7919	0.7203 (0.0363)
I7 (176039)	0.7889 (0.0368)	0.8339 (0.0213)	0.826 (0.0001)	**0.8341**	0.7996 (0.0252)
I8 (178054)	0.7035 (0.0081)	0.7613 (0.0063)	0.7068 (0.0001)	**0.7653**	0.7622 (0.0023)
I9 (216066)	0.7425 (0.0059)	0.7653 (0.0076)	0.7399 (0.0001)	**0.7719**	0.7562 (0.0251)
I10 (353013)	0.8088 (0.0198)	0.8235 (0.0065)	**0.8338** (0.0001)	0.755	0.74 (0.0211)

It is necessary mentioning that all the compared methods produce single output segmented solution. The first two methods are proposed for color images and the last one for gray-scale information. Whereas, our proposed approach produces a set of trade-off segment solutions. The values in bold face are the best and the values within braces are the standard deviation values. Based on *Modified PRI* as mentioned in the table, it is evident that our proposed approach finds the best *Modified PRI* for most of the test images (6 out of 10 images). Moreover, for the other 4 images where our approach can not find the best values, the values obtained by our approach are still satisfactory. In short, the *Modified PRI* values show that our approach can find a number of segments equal to one of the ground-truth segmentations.

From this table, it can also be observed that in some cases the standard deviation values obtained by our approach are relatively large. Considering multi-objective evolutionary optimization, this phenomenon can be considered as "good". It confirms an extra advantage of the proposed approach—its ability to find extreme solutions along the Pareto-front. Finding extreme solutions are, in particular, very important for MOEAs. This is because, the decision maker can select the best compromise solution according to specific segmentation objective required in different cases.

5 Conclusion

This paper presents a multi-objective segmentation approach for color images by optimizing three objectives simultaneously. To quantitatively asses multiple trade-off solutions in terms of test images with multiple ground-truth examples, we also extend an existing performance criteria into a modified performance index (*Modified PRI*). Experimental results justify that our proposed approach is able to segment color images in a number of regions that adhere well to the human visual perception. The quantitative evaluation also shows that our proposed approach is competitive with state-of-the-art methods for color image segmentation. In addition, our proposed approach is capable of searching a set of near-optimal trade-off segmentation solutions while finding the correct number of clusters automatically. This is essential for real-world segmentation as the trade-offs involved in considering several different criteria provide useful insights to decision makers by providing the flexibility to consider a number of criteria before choosing a solution. In the future, we would like to implement other segmentation criteria as optimization objectives to test the effectiveness of each. Implementing other recent MOEAs to analyze their behavior and performance could be another interesting avenue for future works.

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