IT 3708: Project 2

Segmentation of Color Image Using Multi-Objective Evaluation Algorithm (MOEA)

Lab Goals

- Implement multi-objective evaluation algorithm (MOEA) to color image segmentation.
- Compare the performance of your implemented MOEA on several benchmark problems.
- Test and analyze effects of MOEA(s) in optimizing multiple objectives simultaneously.

Groups Allowed? Yes. For this project, you may work alone or in groups of two. Note that, even though, you work in a group, **you must write the report individually and without any collaboration with your group partner, or others**. All students must attend the demo day individually and be prepared for both group and individual work (without collaboration).

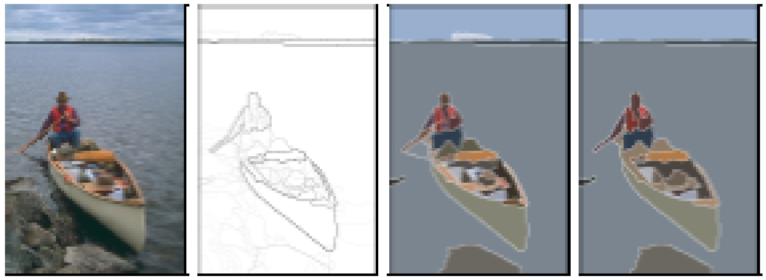
Deadline: March 13, 2018 (Tuesday) at 08: 00 AM.

Assignment Details

In a conventional sense, image segmentation is the partitioning of an image into non-intersecting regions (***sets of pixels***), where pixels within a region are similar according to some uniformity predicate, and dissimilar between neighboring regions. Image segmentation is a fundamental process in many image, video, and computer vision applications, where the segmented regions have two properties: (1) homogeneity within a region, i.e., the texture, color, or intensity of each pixel in a region should be similar to the other, and (2) heterogeneity between the regions, i.e., the texture, color, or intensity of the pixels in one region should be distinct from the pixels in another region. Fig. 1 presents several examples of image segmentation. As shown, the same image can be segmented differently, however, the main goal is to partition an image into separate regions of pixels, which ideally correspond to different real-world objects.

(a)

(b)



(c)

Fig. 1: Image segmentation. Leftmost images are original images, and others are several segmentation examples.

In this project, you will implement **a segmentation technique for color image using MOEA**. You can select any one of the following three MOEAs as your choice: (i) NSGA-II, (ii) SPEA, (iii) PAES. To analyze the effects of MOEAs in handling simultaneous optimization of multiple objectives, you will segment color images using not only your chosen MOEA, **but also the weighted-sum method that will optimize these two criteria (objectives), i.e., a simple GA**.

Problem Formulation:

The first step is to convert the phenotype (image) into genotype (chromosome), which will be processed during the evolutionary process. In most cases, pixels are stored as corresponding color values (RGB or CIE L*a*b as the color space [1]). However, **you are free to choose your own representation** (chromosome and transformation from genotype to phenotype). Note that you should chose the representation carefully as the choice will affect the evolutionary process. There are several existing representation techniques for image segmentation, e.g, graph-based or tree-based representation where you can store all the pixels or only representatives of segments. **You can choose as per your requirement, even you can propose a new one**.

You need to simultaneously optimize two objectives (segmentation criteria) using your chosen MOEA. The objectives are: (i) overall deviation and (ii) edge value.

- The *overall deviation* is a measure of similarity of pixels in the same segment, as defined in Equation (1). It expresses the compactness of segments by giving the overall summed distances between the pixels and the center value of the corresponding segment they belong to.

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

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**. You need to define the distance function *dist( )* as Euclidean distance by using either RGB or CIE L*a*b* [1] as the color space. The distance function using the RGB (δ_{RGB}) and CIE L*a*b* (δ_{L*a*b}) color space is defined in equation (2) and equation (3), respectively.

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

$$\delta_{L*a*b} = \sqrt{\Delta L*^2 + \Delta a*^2 + \Delta B*^2} \tag{3}$$

- The second objective, the *edge value*, is a measure of the difference in the boundary between the segments. **It is subject to maximization** and is defined as:

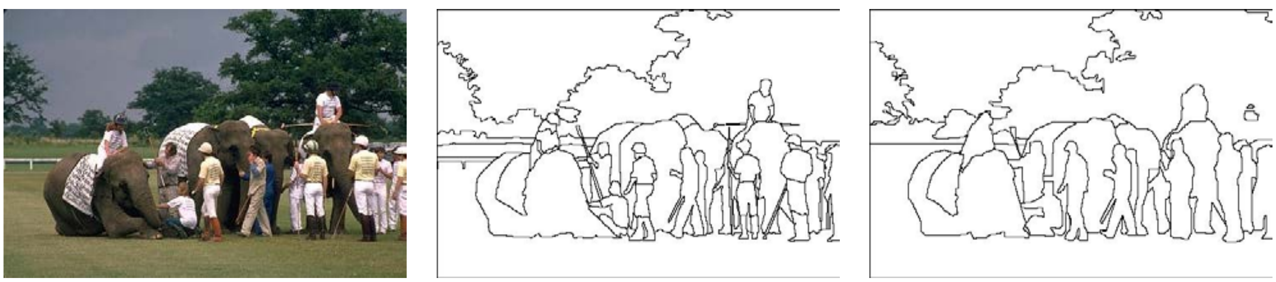
$$\text{Edge}(C) = \sum_{i=1}^{N} \left(\sum_{j \in F_i} x_{i,j} \right),$$

$$\text{where, } x_{c,s} = \begin{cases} dist(c,s) & if \nexists C_k : c,s \in C_k \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where N is the number of pixels, F_i indicates the four neighboring pixels of pixel i, and *dist( )* is the distance function as described in the above objective.

By minimizing these two objectives, a variety of different segmentations for the same image are generated. In other words, your method will return a range of solutions that have different **trade-offs (Pareto-optimal) segmentation solutions for the input test image**.

As mentioned earlier, you also need to implement your segmentation approach by using the **weighted-sum method**. As a result, you should get different segmentations. By comparing the segmentations produced by the weighted-sum method against the Pareto-optimal segmentation produced by the MOEA, you can analyze the effects of MOEA in optimizing multiple objectives.



(a) Test image

(b) Ground-Truth-1 with 106 segments

(c) Ground-Truth-2 with 54 segments

Fig. 2: Ground-truth segmentation examples

Evaluation Criterion

The Berkeley dataset contains multiple human-traced segmentation for each color image, all of which are considered equally reliable. Your comparison should be made against all the manually obtained ground-truth segmentations[1]. Fig. 2 presents examples of such ground-truth examples with different number of segments for one test image. Note that several ground-truth solutions are available for every image, all of which are considered satisfactory segmentation for the test image. For comparison against multiple ground truth of the same test image, Probalistic Rand Index (PRI) is used to assess the quality of the produced segmentation. However, PRI was designed to evaluate the segmentation approaches that produce a single final segmented solution. This project aims to find a set of Pareto-optimal segmented outputs instead of a single segmented output image by simultaneous optimization of two objectives.

For this multiple-objective approach, the PRI needs to be modified. Given a set $\{GT_1, GT_2, \ldots, GT_T\}$ of ground-truth segmentations of an image I consisting of n pixels, and a set of Pareto-optimal segmentation

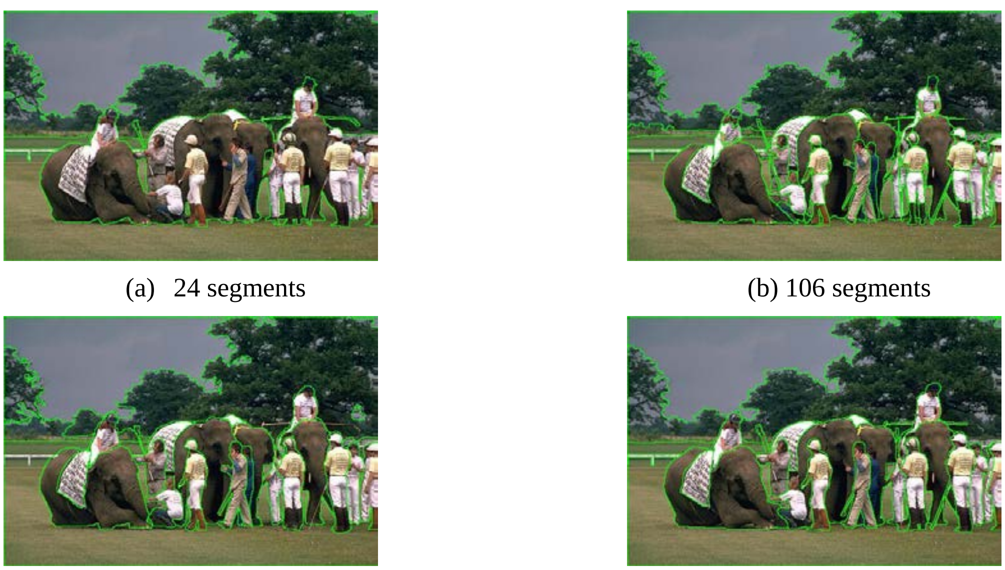
[1] Ground truth segmentation solutions: the segmented solution of the test image that is known to be very accurate solution. Basically, it is created by segmenting the image by lots of human subjects (including both experts and non-experts). Then the ground-truth is created considering all the segmented solutions.

results $\{I_1, I_2, ..., Ip\}$ produced by your implementation, the Modified PRI will compare every member of your produced Pareto-optimal segmentation set against every ground-truth segmentations of that image. Ultimately, it will find the best segmentation solution among your produced Pareto-optimal set based on the best PRI value. For your reference, this modified PRI takes values in [0, 1], where 0 means no similarities with ground-truths (i.e., over or under segmentation) and 1 means identical segmentation (excellent segmentation). You can find more about PRI in [2].

The coding for modified PRI along with the test images and achieved best (so far) modified PRI values are uploaded. Note that, the **modified PRI values will be calculated based on the produced segmentation type mentioned in Fig. 3c**.

(a) Test image (b) Required solution type - 1 (c) Required solution type - 2

Fig. 3: Examples for your requirement



(a) 24 segments (b) 106 segments

(c) 54 segments (d) 42 segments

Fig. 4: Different segmentation of the same image

Things To Do

The 20 points total for this project are 20 of the 100 points available for this course. The 20 points will be distributed in two parts: (*i*) demo and (*ii*) report. **The demo can give you a maximum of 12 points and the report can give you a maximum of 08 points**.

To test your code, we uploaded 08 benchmark images, their ground-truth segmentation solutions, and corresponding so far achieved best modified PRI values. **You need to produce two types of segmentation solutions (for each member of Pareto-optimal solution set) for each test image.** Fig. 3 presents the requirements. As shown in the figure, for the original image (Fig. 3a), you need to produce two types of segmentation (Fig. 3b and 3c). Two of the available ground truth solutions for this image are presented in Fig. 2b and 2c. One image can be segmented differently with different numbers segments. Fig. 4 illustrates different reasonable "good" segmentations for the test image presented in Fig. 3a.

In this project, you need to implement segmentation approach for color image optimizing the mentioned two objectives using any one of the three MOEAs mentioned earlier. You also need to **implement your segmentation using weighted-sum method to optimize these objectives.**

(a) Demo (12p):

There will be a demo session where you will show us the running code and we will verify that it works. Even though you work in a group, **both must attend the demo individually on the scheduled demo date**. In the demo session, you need to describe how you designed and implemented your MOEA. Also, you have to test you code by running 04 (four) test images that you will be supplied during the demo (3 test images to check the performance of your implementation + 1 test image to explain your implementation and for weighted-sum method). **You must run your code and show us all the requirements (including the explanation) within 30 (thirty) minutes**. During demo, we will provide you the lowest and the highest number of possible segments for each test image. Your implementation can have this option as input, if you wish.

The point distribution for the demo is as follows:

(1) You need to optimize two objectives simultaneously for three test images. (7.5 = 2.5 x 3)

- For each test image:
  - ❖ PRI Value (2.5p)
    - o If PRI value is greater than 0.65, you will get full points.
    - o If PRI value is greater than 0.60, you will get 1.5 points.
    - o If PRI value is greater than 0.55, you will get 1 point.
    - o Otherwise, you will get 0.

(2) For all the test images, show the segmented solutions along with respective objective values and segment number (for all members of the final Pareto-optimal solutions). If the final Pareto-optimal solutions are more than 5, you can show any 5 of them. For each of the presented segmented solutions, you need to show both types of segmentation for the same solution (Fig. 3b and 3c). (1p)

(3) Present the Pareto-front consisting of the two objectives for any one of the three test images. (0.5p)

∗ **You can only get a maximum of 1 point per test image for Demo Section 1, if your output segmentation does not follow both types of segmentation (Fig. 3b and 3c) for the same solution.**

(2) Explanation (3p)

- You will be provided with an extra test image that needs to be run using the weighted-sum method as well as your implemented MOEA. Based on the achieved PRI values, you need to be ready to explain the reason behind the differences in segmentation quality obtained by MOEA and weighted-sum method.

(b) Report (08p):

You should write a report answering the points below. Your report must not exceed 03 (Three) pages in total. **Over length reports will result in points being deducted from your final score**. Print on both sides of the sheet, preferably. **Bring a hard copy of your report to the demo session**. If you work in a group, you must write the report individually without any collaboration with your group partner and submit your own report.

1. Different MOEAs utilize different strategies to handle multiple objectives (as discussed in Lecture 5 along with additional slides for lecture 5). Your implemented MOEA has a certain strategy. In comparison to any one of the other two mentioned MOEAs, why do you think the strategy in your implemented MOEA is better? If not, why not? (3p)
2. Describe the Chromosome representation that you used in your implementation. Also, mention another representation that could be used for this problem and why this representation is also suitable. Defend your choice of the most suitable representation. (2p)
3. Using different set of weights in the weighted-sum method, explain the effects of weights in optimizing two objectives that you observed during your implementation. You need to justify your answer using proper numerical data. You can also use figures (if necessary). (3p)

Delivery

You should deliver your report + a zip file of your code on *BlackBoard*. The submission system will be closed at 08:00 AM on March 13, 2018. **If you work in a group, you must submit individually,** mentioning your group partner's name in the report (precisely as your group partner). **Each must attend the demo individually on the scheduled demo date**, which have been already declared on *BlackBoard*. **No early or late demo will be entertained except for extreme emergency**.

References:

[1] Gunther Wyszecki and W. S. Stiles. Color Science: Concepts and Methods, Quantitative Data and Formulae, 2nd Edition. Wiley Interscience, 2000.

[2] Unnikrishnan, Ranjith, Caroline Pantofaru, and Martial Hebert. "Toward objective evaluation of image segmentation algorithms." *IEEE transactions on pattern analysis and machine intelligence* 29.6 (2007): 929-944.

NB:

1. Every question regarding this project will **only be handled** through the Slack channel.
2. Playing with images may require your programming language handling large memory. Therefore, you need to be tricky while choosing your programming language.