Region Merging for Severe Oversegmented Images using a Hierarchical Social Metaheuristic

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Abstract. This paper proposes a new evolutionary region merging method to improve segmentation quality result on oversegmented images. The initial segmented image is described by a modified Region Adjacency Graph model. In a second phase, this graph is successively partitioned in a hierarchical fashion into two subgraphs, corresponding to the two most significant components of the actual image, until a termination condition is met. This graph-partitioning task is solved as a variant of the min-cut problem (normalized cut) using a Hierarchical Social (HS) metaheuristic. We applied the proposed approach on different standard test images, with high-quality visual and objective segmentation results.

1 Introduction

Image segmentation is one of the most complex stages in image analysis. It becomes essential for subsequent image description and recognition tasks. The problem consists in partitioning an image into its constituent regions or objects [1]. The level of division depends on the specific problem being solved. The segmentation result is the labelling of the image pixels that share any property (brightness, texture, colour…). The oversegmentation, which occurs when a single semantic object is divided into several regions, is a tendency of some segmentation methods like watersheds [2,3]. Therefore, some subsequent region merging process is needed to improve the segmentation results.

The proposed segmentation method can be considered as a region-based one and pursuits a high-level extraction of the image structures. After a required oversegmentation of the initial image, our method produces a hierarchical top-down region-based decomposition of the scene. The way to solve the segmentation problem is a pixel classification task, where each pixel is assigned to a class or region by considering only local information [1]. We take into account this pixel classification approach by representing the image as a simplified weighted graph, called Modified Region Adjacency Graph (MRAG). The application of a Hierarchical Social (HS) metaheuristic [4] to efficiently solve the normalized cut (NCut) problem for the image

MRAG is the core of the proposed method. An evident computational advantage is obtained describing the image by a set of regions instead of pixels in the MRAG structure. It enables a faster region merging in images with higher spatial resolution.

Today, the applications of evolutionary techniques to Image Processing and Computer Vision problems have increased mainly due to the robustness of these methods [5]. Evolutionary image segmentation [6,5,7] has reported a good performance in relation to more classical segmentation methods. Our approach of modelling and solving image segmentation as a graph-bipartitioning problem is related to Shi and Malik's work [8]. They use a computational technique based on a generalized eigenvalue problem for computing the segmentation regions. Instead, we found that high quality segmentation results can be obtained when applying an HS metaheuristic to image segmentation through a normalized cut solution.

2 Modified Region Adjacency Graph

Several techniques have been proposed to decrease the effect of oversegmentation on watershed-based approaches [2,3]. These usually involve a preprocessing of the original image. Many of them are based on the Region Adjacency Graph (RAG) which is a usual data structure for representing region neighbourhood relations in a segmented image [9].

As stated in [8,10] the image partitioning task is inherently hierarchical and it would be appropriate to develop a top-down segmentation strategy that returns a hierarchical partition of the image instead of a flat partition. Our approach shares this perspective and provides as segmentation result an adaptable tree-based image bipartition where the first levels of decomposition correspond to major areas or objects in the segmented image.

The MRAG structure takes advantage of both, region-based and pixel-based representations [8,11]. The MRAG structure is an undirected weighted graph $G=\{V,E,W\}$, where the set of nodes (V) represents the set of centres-of-gravity of each region. These regions result from the initial oversegmentated image. The set of edges (E) are the relationships between pairs of regions, and the edge weights (W) represent a similarity measure between pair of regions. In this context, the segmentation problem can be formulated as a graph bipartition problem, where the set V is partitioned into two subsets V_1 and V_2, with high similarity among vertices inside each subset and low similarity among vertices of different subsets.

As starting hypothesis, we suppose that each initial pre-segmented region must be small enough in size with respect to the original image and not having much semantic information. Some characteristics of the MRAG representation that yield to some advantages respect to RAG are:

1) It is defined once and it does not need from any dynamic updating when merging regions.

2) The number of pixels associated to each MRAG node (size of initial oversegmented regions) must be approximately the same.

3) MRAG-based segmentation approach is hierarchical and the number of final regions is controlled by the user according to the required segmentation precision.

4) The segmentation, formulated as a graph partition problem, leads to the fact that extracted objects are not necessarily connected.

The set of edge weights reflects the similarity between each pair of related regions (nodes) v_i and v_j. These connected components may or may not be adjacent, but if they are not adjacent, these components are close than a determined distance threshold r_x. The weights $w_{ij} \in W$ are computed by the conditional function:

$$if\ \left(\left|x_i - x_j\right| < r_x\right)\ then\ w_{ij} = e^{\frac{-C_{ij}(I_i - I_j)^2}{\sigma_I^2}} \cdot e^{\frac{-C_{ij}(x_i - x_j)^2}{\sigma_x^2}}\ else\ w_{ij} = 0 \tag{1}$$

where r_x, σ_x and σ_I are experimental values, I_i is the mean intensity of region i, and x_i is the spatial centre-of-gravity of that region. Finally, the factor C_{ij} takes into account the cardinality of the regions i and j. This value is given by:

$$C_{ij} = \frac{\| E_i \| \cdot \| E_j \|}{\| E_i \| + \| E_j \|} \tag{2}$$

where $||E_i||$, $||E_j||$ are, respectively, the number of pixels in regions v_i and v_j. Non-significant weighted edges, according to the defined similarity criteria, are removed from the image graph.

3 Image Partitioning Via Graph Cuts

The recent literature has witnessed two popular image graph-based segmentation methods: the minimum cut (and their derivates) using graph cuts analysis [8,12,13] and the energy minimization, using the max flow algorithm [14,15]. More recently, it has been proposed a third major approach based on a generalization of Swendsen-Wang method [16]. In this paper, we focus on min-cut approach because they can be easily solved with an HS metaheuristic.

The min-cut optimization problem, defined for a weighted undirected graph $S=(V,E,W)$, consists in finding a bipartition G of the set of nodes of the graph: $G=(C,C')$ such that the sum of the weights of edges with endpoints in different subsets is minimized. Every partition of vertices V into C and C' is usually called a cut or cutset and the sum of the weights of the edges is called the weight of the cut or similarity (s) between C and C'. For the considered min-cut optimization problem, it is minimized the cut or similarity s, between C and C':

$$w(C,C') = s(C,C') = \sum_{v \in C, u \in C'} w_{vu} \tag{3}$$

In [17] is demonstrated that the decision version of Max-Cut (dual version of Min-Cut problem) is NP-Complete. This way, we need to use approximate algorithms for finding the solution in a reasonable time.

The Min-Cut approach has been used by Wu and Leahy [13] as a clustering method and applied to image segmentation. These authors look for a partition of the graph into k subgraphs such that the similarity (min-cut) among subgraphs is minimized. They pointed out that although in some images the segmentation is acceptable; in general, this method produces an oversegmentation because small regions are favoured. To avoid this fact, in [18] other functions that try to minimize the effect of this problem are proposed. The optimization function called min-max cut is:

$$cut(G) = \frac{\sum_{v\in C,u\in C'} w_{vu}}{\sum_{v\in C,u\in C} w_{vu}} + \frac{\sum_{v\in C,u\in C'} w_{vu}}{\sum_{v\in C',u\in C'} w_{vu}} = \frac{s(C,C')}{s(C,C)} + \frac{s(C,C')}{s(C',C')} \tag{4}$$

where the numerators of this expression are the similarity $s(C,C')$ and the denominators are the sum of the arc weights belonging to C or C', respectively. It is important to remark that in an image segmentation framework, it is necessary to minimize the similarity between C and C' (numerators of eq. 2) and maximize the similarity inside C, and inside C' (denominators of eq. 2). In this case, the sum of arcs between C and C' is minimized, and simultaneously the sums of weights inside of each subset are maximized. Other authors [2] propose an alternative cut value called *normalized cut (NCut)*, which, in general, gives better results in practical image segmentation problems. Mathematically this cut is defined as:

$$Ncut(G) = \frac{\sum_{v\in C,u\in C'} w_{vu}}{\sum_{v\in C,u\in C\cup C'} w_{vu}} + \frac{\sum_{v\in C,u\in C'} w_{vu}}{\sum_{v\in C',u\in C\cup C'} w_{vu}} = \frac{s(C,C')}{s(C,G)} + \frac{s(C,C')}{s(C',G)} \tag{5}$$

where $G = C \cup C'$.

4 Hierarchical Social (HS) Algorithms

This section shows general features of a new evolutionary metaheuristic called hierarchical social (HS) algorithm. In order to get a more general description of this metaheuristic, the reader is pointed to references [4,19,20,21,22]. This metaheuristic has been successfully applied to several problems such as: critical circuit computation [22], scheduling [4,21], MAX-CUT problem [19] and region-based segmentation[20].

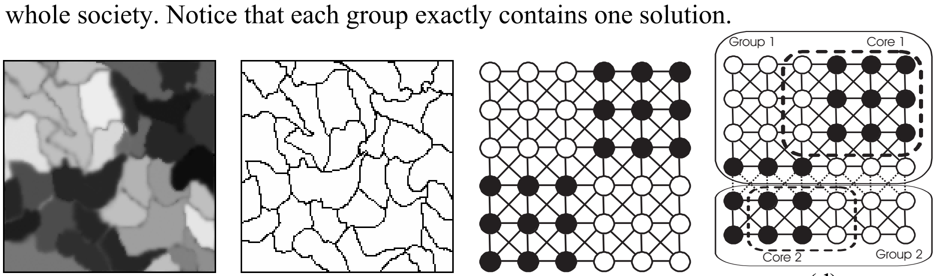
HS algorithms are inspired in the hierarchical social behaviour observed in a great diversity of human organizations. The key idea of HS algorithms consists in a simultaneous optimization of a set of disjoint solutions. Each group of a society contains a feasible solution. These groups are initially randomly distributed to produce a disjoint partition of the solution space. Better solutions are obtained using intra-group cooperation and inter-group competition as evolution strategies. Through this process groups with lower quality tend to disappear. As a result, the objective functions of winners groups are optimized. The process typically ends with only one group that contains the best solution.

4.1 Metaheuristic structure

For the image segmentation problem, the feasible society is modelled by the specified undirected weighted graph, also called feasible society graph. The set of individuals are modelled by nodes of the graph V and the set of feasible relations are modelled by edges E of the specified graph. The set of similarity relations are described by the weights W. Notice that when the graph also models an image, nodes represent initial watershed resulting regions and edges model the similarity between these regions.

Figure 1.a shows an example of a feasible society graph, which represents a simple synthetic image with two major dark and white squares. This image is a noisy and deformed chess board. In figure 1.b is shown the watershed segmentation of the image presented in figure 1.a. In this image there are 36 regions, 9 regions in each square. Figure 1.c shows the MRAG built from the watershed image. Obviously, the graph has 36 nodes.

The state of a society is modelled by a hierarchical policy graph [4,22]. This graph also specifies a society partition composed by a disjoint set of groups $\Pi=\{g_1,g_2,\ldots,g_g\}$, where each individual or node is assigned to a group. Each group $g_i \subset S$ is composed by a set of individuals and active relations, which are constrained by the feasible society. The individuals of all groups cover the individuals of the whole society. Notice that each group exactly contains one solution.



(a) (b) (c) (d)

Fig. 1. (a) Synthetic chess board image. (b) Watershed segmentation. (c) Feasible society graph. (b) Society partition and groups partition

The specification of the hierarchical policy graph is problem dependent. The initial society partition determines an arbitrary number of groups and assigns individuals to groups. Figure 1.d shows a society partition example formed by two groups.

Each individual of a society has two objective functions: *individual objective function f1* and *group objective function f2* that is shared by all individuals in the same group. Furthermore each group g_i is divided into two disjoint parts: *core* and *periphery*. The core determines the value of the corresponding group objective function *f2* and the periphery defines the alternative search region of the group.

In the image segmentation framework, the set of nodes of each group g_i is divided into two disjoint parts: $g_i = (C_i, C'_i)$ where C_i is the core or group of nodes belonging to the considered cutset and C_i' is the complementary group of nodes. The core edges are the arcs that have their endpoints in C_i and C_i'. Figure 1.d also shows an example of core for the previous considered partition. The core nodes of each group are delimited by one dotted line. For each group of nodes $g_i = (C_i, C'_i)$, the group objective function *f2*(i) is given by the corresponding normalized cut *Ncut*(i) referred to the involved group g_i:

$$f2(i) = NCut(i) = \frac{\sum_{v \in C_i, u \in C_i'} w_{vu}}{\sum_{v \in C_i, u \in C_i \cup C_i'} w_{vu}} + \frac{\sum_{v \in C_i, u \in C_i'} w_{vu}}{\sum_{v \in C_i', u \in C_i \cup C_i'} w_{vu}} = \frac{s(C_i, C_i')}{s(C_i, g_i)} + \frac{s(C_i, C_i')}{s(C_i', g_i)} \qquad (6)$$

$$\forall v \in g_i \quad f2(v,i) = f2(i) = NCut(i)$$

where $gi = Ci \cup Ci'$ and the weights w_{vu} are supposed to be null for the edges that do not belong to the specified graph.

For each individual or node v, the individual objective function $f1(v,i)$ relative to each group g_i is specified by a function that computes the increment in the group objective function when an individual makes a movement. There are two types of movements: *intra-group movement* and *inter-group movement*. In the intra-group movement there are two possibilities: the first one consists in a movement from $\boldsymbol{C_i}$ ***to*** $\boldsymbol{C_i'}$, the second one is the reverse movement ($\boldsymbol{C'_i}$ ***to*** $\boldsymbol{C_i}$).

The inter-group movement is accomplished by an individual v that belongs to a generic group g_x ($g_x = \Pi \setminus g_i$) that wants to move from g_x to g_i. There are two possibilities: the first one consists in a movement from $\boldsymbol{g_x}$ ***to*** $\boldsymbol{C_i}$, the second one consists in a movement from $\boldsymbol{g_x}$ ***to*** $\boldsymbol{C'_i}$.

The next formula shows the incremental computation of the individual function $f1$ for the movement $C_i \rightarrow C'_i$.(described by the function $C\_to\_C'(v,i)$).

$$f1(v,i) = C\_to\_C'(v,i) = \frac{s(C_i,C_i') - \sigma'(i) + \sigma(i)}{s(C_i,gi) - \sigma'(i)} + \frac{s(C_i,C_i') - \sigma'(v,i) + \sigma(v,i)}{s(C_i',g_i) + \sigma(v,i)} \qquad (7)$$

$$\text{where} \quad \sigma(v,i) = \sum_{u \in C_i} w_{vu} \ \ and \ \ \sigma'(v,i) = \sum_{u \in C_i'} w_{vu}$$

The other movements ($C'_i \rightarrow C_i$, $X \rightarrow C_i$,$X \rightarrow C'_i$) have similar expressions. During a competitive strategy, function $f1$ allows selecting for each individual v, the group that achieves the corresponding minimum value.

The HS algorithms here considered, try to optimize one of their objective functions ($f1$ or $f2$) depending on the operation phase. During cooperative phase, each group g_i aims to improve independently the group objective function $f2$. During a competitive phase, each individual tries to improve the individual objective function $f1$, the original groups cohesion disappeared and the graph partition is modified in order to optimize the corresponding individual objective function.

4.2 Metaheuristic process

The algorithm starts from a random set of feasible solutions. Additionally for each group, an initial random cutset is derived. The groups are successively transformed through a set of social evolution strategies. For each group, there are two main strategies: *intra-group cooperative strategy* and *inter-group competitive strategy*. The first strategy can be considered as a local search procedure in which the quality of the solution contained in each group is autonomously improved. This process is maintained during a determined number of iterations (autonomous iterations).

The intra-group competitive strategy can be considered as a constructive procedure and is oriented to let the interchange of individuals among groups. In this way the groups with lower quality tend to disappear because their individuals move from these groups to another ones with higher quality.

Cooperative and competitive strategies are the basic search tools of HS algorithms. These strategies produce a dynamical groups partition, where group annexations and extinctions are possible. A detailed description of HS algorithms, cooperative strategy and competitive strategy and their corresponding pseudo-codes can be found in [4].

5 Method Overview

Figure 2 outlines the three major stages considered in the proposed evolutionary segmentation approach. First, we create an over-segmented image applying a standard watershed segmentation to the initial brightness image.

In the second stage, the corresponding MRAG for the oversegmented image is built. This graph is defined by representing each resulting region by a unique node and defining the edges and corresponding edge weights as a measure of spatial location, grey level average difference and cardinality between the corresponding regions (see Eq.1 in Section 2).

The third major stage consists in iteratively applying the considered HS metaheuristic in a hierarchical fashion to the corresponding subgraph, resulting from the previous graph bipartition, until a termination condition is met. This stage itself constitutes an effective region merging for oversegmented images.

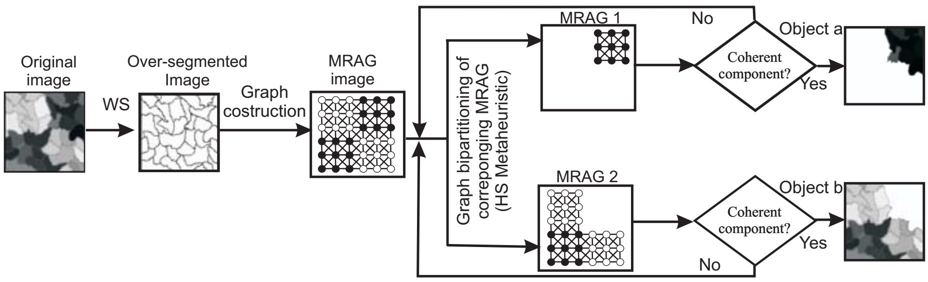


Fig.2 Block diagram of the proposed method.

6 Experimental Results

Table 1 shows the standard test images used, the characteristics of the corresponding MRAG and the value of the first *NCut* after the application of the HS metaheuristic. Considered characteristics of MRAG are: number of nodes (regions of the watershed oversegmented image), number of edges and parameters of the weight function (σ_I, σ_x, r_x). The last column shows the first *NCut* value for the first MRAG bipartition, which can be considered as a quantitative measure of the segmentation quality [8].

Table 1: Image characteristics and quantitative results

	MRAG	***MRAG Parameters***				***HSA***
Image	*Nodes*	*Arcs*	σ_I	σ_x	r_x	*NCut*
Lenna256x256	7156	1812344	200	200	40	0.0550
Windsurf480x320	11155	1817351	200	200	35	0.0396
Cameraman256x256	4181	460178	100	200	35	0.0497

Figure 3.a shows the input image (*Lenna*), its corresponding oversegmented image. Figure 3.b shows the obtained oversegmentation by means of a watershed algorithm. The resulting segmentation tree (Figure 3.c) gives a hierarchical view of the

segmentation process. In the first phase of the algorithm, the original image is split into two parts (Figures 3.d and 3.h). Notice that the segmented objects are not connected. This property is especially interesting in images with partially occluded objects, noisy images, etc.

The most important part (Figure 3.d) is split again, obtaining the images presented in Figure 3.e and 3.i. As in the previous case, the most significant region (Figure 3.e) is split again, obtaining the images 3.f and 3.j. This process can be repeated until a determined minimum *NCut* value is obtained or the process is stopped by the user. The segmented image is given by the union of the final components. The resulting objects correspond to the tree segmentation leafs. For *Lenna* image, a high segmentation quality is achieved. Note that the images presented in the rest of figures (Figures 3.g, 3.h, 3.i, 3.j and 3.k) could be also bipartitioned, in order to achieve a more detailed segmentation.

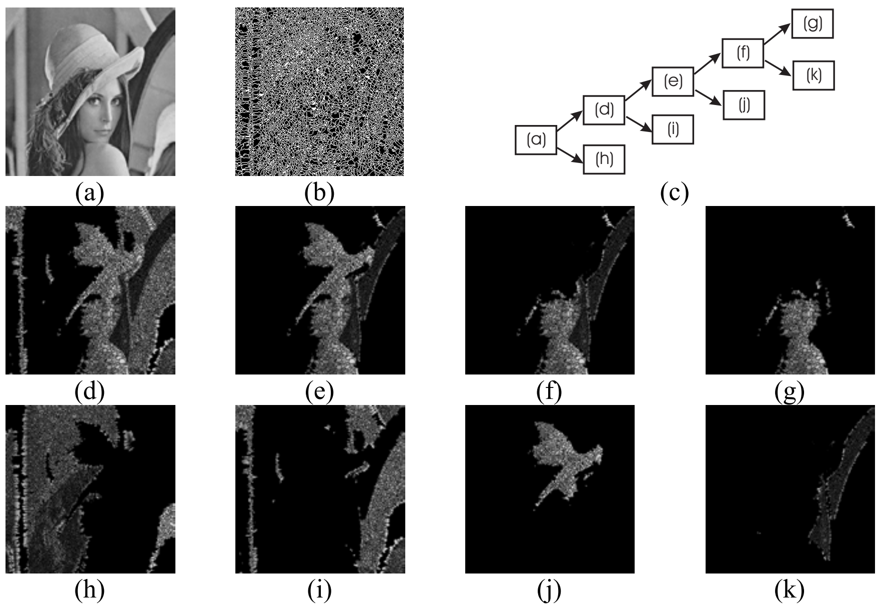


Fig. 3. Segmentation results for image *Lenna*: (a) Initial image. (b) Watershed segmentation (c) Structure of the segmentation tree. (d),...,(k) Resulting segmented regions according to the segmentation tree

The segmentation process can have some peculiarities relative to the obtained *NCut*. Sometimes, the obtained segmentation contains spurious cuts that do not correspond to objects. An example of this phenomenon can be observed in Figure 4.h, where the background is segmented into two regions.

This fact occurs because *NCut* favours approximately equal size cuts. Sometimes, these spurious cuts do not affect the segmentation results, as in this case, because in the next cut it is extracted the rest of the main information. If an important object has been split, the algorithm can not correctly extract the corresponding object. In this case, a different choice of the edge weights (similarity measure) or metaheuristic parameters should be considered to improve the segmentation results.

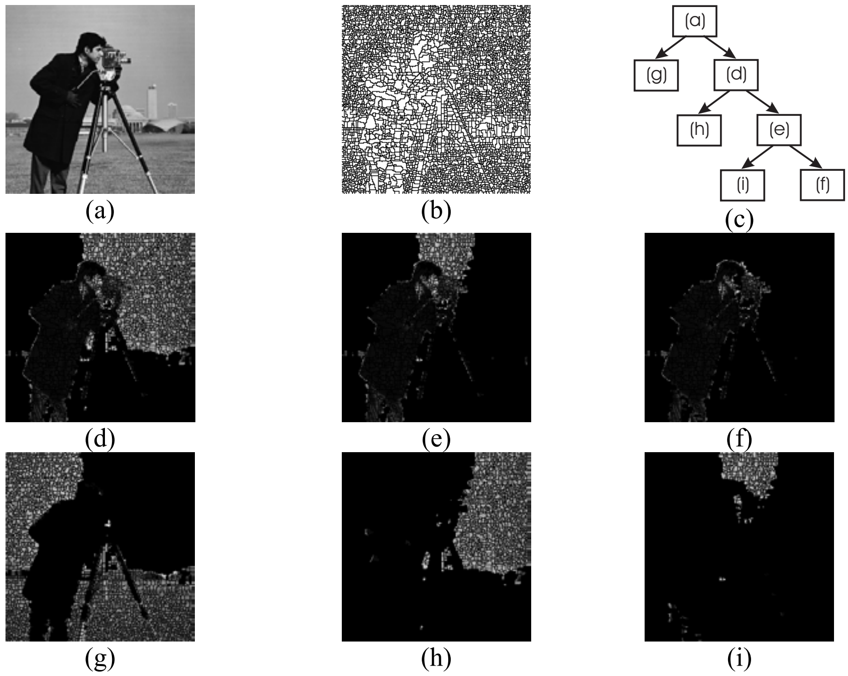


Fig. 4. Segmentation results for image *Cameraman*: (a) Initial image. (b) Watershed segmentation (c) Structure of the segmentation tree. (d),…,(i) Resulting segmented regions according to the segmentation tree

7 Conclusions

This paper has introduced an HS metaheuristic, as a region merging technique, to efficiently improve the image segmentation quality results. Also, a new RAG is proposed, called MRAG. This representation considers neighbourhood relations between pair of regions that are not adjacent. This new model allows the processing of larger spatial resolution images than other typical graph-based segmentation methods [10, 8]. The image problem is now equivalent to minimize the *NCut* value in the corresponding MRAG. As we have experimentally shown, the HS algorithms provide an effective region merging method for achieving high quality segmentation. An important advantage of the approach is that MRAG structure does not need to be updated when merging regions. Moreover, the resulting hierarchical top-down segmentation is adaptable to the complexity of the considered image.

The capability of the method can be improved by decomposing the image at each level of the segmentation tree in more than two regions. In this case the *NCut* value is not an adequate group objective function, because it is not defined for several cuts. We propose as a future work the use of other group objective functions in order to exploit all the potential of HS metaheuristics for segmentation applications.

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