# A Combination of Histogram of Oriented Gradients and Color Features to Cooperate with Louvain Method based Image Segmentation

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Keywords: Image Segmentation, Complex Networks, Modularity, Superpixels, Louvain Algorithm, Community Detection.

Abstract: This paper presents an image segmentation strategy using histograms of oriented gradients *(HOG)*, color features and Louvain method, a community detection on graphs algorithm, to tackle the image segmentation problem. This strategy relies on the use of community detection based image segmentation which often leads to over-segmented results. To address this problem, we propose an algorithm that agglomerates homogeneous regions using texture and color features properties. The proposed algorithm is tested on the publicly available Berkeley Segmentation Dataset *(BSDS300 and BSDS500)*, and the Microsoft Research Cambridge Object Recognition Image Database *(MSRC)* datasets. The experimental results point out that our method produces sizable segmentation and outperforms almost other known methods in terms of accuracy and comparative metrics scores.

## 1 INTRODUCTION

Image segmentation has become an indispensable task that is widely employed in several image processing applications including object detection (Liu and Chen, 2008), object tracking (Zhou et al., 2000), automatic driver assistance (Chen et al., 2008), and traffic control systems (Junwei and Shaokai, 2013), *etc.* The goal of image segmentation is not only to distinguish the interesting objects from the background, but also to identify them in an image. A variety of proposed algorithms have dealt with image segmentation in the literature. These methods can be divided into some main groups according to the underlying approaches, such as feature-based clustering, spatial-based segmentation methods, hybrid techniques and graph-based approaches.

Recently, complex networks have mushroomed both theories and applications as a trend of developments. Hence, image segmentation techniques based on community detection algorithms have been proposed and have become an interesting discipline in the literature (Youssef Mourchid, Mohammed El Hassouni and Hocine Cherifi, 2015; Youssef Mourchild, Mohammed El Hassouni and Hocine Cherifi, 2016; Abin et al., 2011; Li and Wu, 2015; Mourchid et al., 2017; Linares et al., 2016; Li, 2013; Browet et al., 2011). A community is a group of nodes with dense internal connections and sparse connections with members of other communities. The general idea of those techniques is to highlight the similarity between the modularity criterion in network analysis and the image segmentation process. In fact, the larger the modularity of a network is, the more accurate the detected communities, *i.e.*, the objects in the image, are (Browet et al., 2011; Youssef Mourchid, Mohammed El Hassouni and Hocine Cherifi, 2015; Mourchid et al., 2017; Abin et al., 2011). If the modeling of the image in a graph is well done then we can expect that a good partition in communities corresponds to a good segmentation of the image. The modularity of a partition is a scalar that measures the density of links inside communities as compared to links between communities, and its value falls into the interval [-0.5,1] (Newman and Girvan, 2004).

Among all the existing community detection algorithms, the Louvain method (Blondel et al., 2008) has received significant attention in the context of image segmentation (Li and Wu, 2015; Youssef Mourchild, Mohammed El Hassouni and Hocine Cherifi, 2016; Browet et al., 2011). However, it is still facing a problem of over-segmentation. In this paper, we propose a new segmentation approach based on the Louvain method that agglomerates homogeneous regions



Nguyen, T., Coustaty, M. and Guillaume, J.
A Combination of Histogram of Oriented Gradients and Color Features to Cooperate with Louvain Method based Image Segmentation.
DOI: 10.5220/0007389302800291
In *Proceedings of the 14th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2019)*, pages 280-291
ISBN: 978-989-758-354-4

in order to overcome the over-segmentation problem. Each sub-segment obtained during the Louvain method phase represents a region. We compute a histogram of oriented gradients (HOG) (Dalal and Triggs, 2005), and the values of mean and standard deviation are computed from the three color channels RGB individually. Then, the proposed algorithm operates by considering the similarity value between two adjacent regions based on combining HOG and color features in order to control the aggregation processes.

The rest of this paper is organized as follows. In Section 2, we briefly review graph-based image segmentation methods. In Section 3, we introduce complex networks, the concept of community detection and Louvain algorithm to point out how community detection algorithms can be applied in image segmentation efficiently. In Section 4, we give details of our method for implementation and performance. Experiments on three publicly available datasets are reported in Section 5. Finally, our conclusions are presented in Section 6.

## 2 RELATED WORK

In this Section, we briefly review some well-known graph-based image segmentation methods.

Considering image segmentation problem from the perspective of graph partitioning has interested several researchers. In this approach, the image is regarded as an undirected weighted graph in which each node represents a pixel, and edge weights measure the similarity between nodes, *i.e.*, similarity between pixels. The graph is clustered by optimizing any adequate criteria, *e.g.*, minimum cut, normalized cut or related variants. (Shi and Malik, 2000).

Felzenszwalb and Huttenlocher (Felz-Hutt) (Felzenszwalb and Huttenlocher, 2004) attempt to partition image pixels into components. Constructing a graph in which pixels are nodes, and edge weights measure dissimilarity between nodes (*e.g.*, color differences), each node is initially placed in its own component. The internal difference of a component $Int(R)$ has been defined as the largest weight in the minimum spanning tree of $R$. Considering in non-decreasing order by weight of edges, each step of the algorithm merges components $R_1$ and $R_2$ connected by the current edge if the weight of the edge is less than:

$$min(Int(R_1)+\tau(R_1), Int(R_2)+\tau(R_2)) \qquad (1)$$

where $\tau(R) = k/|R|$, $k$ is a scale parameter that can be used to set a preference for component size.

Recently, complex networks analysis domain has been considered to segment images, and has achieved outstanding results (Mourchid et al., 2017; Linares et al., 2016; Abin et al., 2011; Li and Wu, 2015). The idea that community detection can be used for image segmentation offers a new perspective.

Wenye Li (Li, 2013), and Youssef, *et al.* (Youssef Mourchild, Mohammed El Hassouni and Hocine Cherifi, 2016) attempt to apply community detection problems in complex networks to solve image segmentation problems, and investigate a new graph-based image segmentation as well as compare other methods. These studies point out the potential perspective of community detection based image segmentation domain.

The image segmentation approaches of Ahmad Ali Abin *et al.* (Abin et al., 2011), and Oscar A. C. Linares *et al.* (Linares et al., 2016) are constructing weighted networks in which the small homogeneous regions *(super-pixels)* obtained by initial segmentation processes are nodes of the graph, and the computed similarity distances between these regions are edge weights. One community detection method is applied to extract communities as segments.

Shijie Li, *et al.* (Li and Wu, 2015), and Youssef Mourchid, *et al.* (Mourchid et al., 2017) propose using super-pixel and features to solve the over-segmentation problem. Both strategies initialize with an over-segmented image segmentation in which each subsegment represents a super-pixel. Then, they treat the over-segmentation issue in different ways. Shijie Li, *et al.* solve it by reconstructing the neighborhood system for each region *(super-pixel)* and the histogram of states *(HoS)* texture feature. Then, they estimate the distribution of the color feature for each region. The similarity matrix $W$ is computed and adaptively updated based on color feature and histogram of states *(HoS)* texture feature. Youssef Mourchid, *et al.* approach the over-segmented problem in a quite similar way but they compute coefficients to adaptively update the similarity matrix $W$ based on color feature and histogram of oriented gradients *(HOG)* texture feature.

## 3 DESCRIPTION OF APPROACH

We consider images from the perspective of a complex network, and solve the image segmentation problem using community detection on graphs. The complex network is built by considering that each pixel is a vertex, and edge weight measures the similarity of a pair of pixels. Then, the Louvain algorithm is applied to the obtained network but this method does not overcome the over-segmentation problem. Our algorithm is therefore built on top of the Louvain method, using HOG and color features so as to avoid this drawback and produce more accurate results.

## 3.1 Complex Networks

A complex network is a graph (network) whose topological structure cannot be trivially described. It comprises properties that emerge as a consequence of global topological organization of the system. Complex network structures describe various systems of high technological and intellectual importance, such as the Internet, World Wide Web, financial, social, neural, and communication networks. One property that has attracted particular attention is the community structure of these networks.

The problem of community detection is usually defined as finding the best partition (or covering) of a network into communities of densely connected nodes, with the nodes belonging to different communities being only sparsely connected. Several algorithms have been proposed to find good partitions in a fast way. These algorithms can be divided into some main types such as, divisive algorithms that detect inter-community links and remove them from the network, agglomerative (or hierarchical clustering) algorithms that merge similar or close nodes and more generally optimization methods are based on the maximization of an objective function (Fortunato, 2010). The qualities of partitions resulting from these methods are often measured by the modularity that has been introduced by Newman and Girvan (Newman and Girvan, 2004). It is defined as follows:

$$Q = \sum_i (e_{ii} - a_i^2) \tag{2}$$

where $e_{ii}$ denotes the fraction of edges in community $i$ and $a_i$ if the fraction of ends of edges that belong to $i$. The value of modularity Q ranges in [-0.5,1] and higher values indicate stronger community structure of the network. Figure 1 shows a partitioning into two communities of a real-world graph.

## 3.2 From Images to Complex Networks

Complex networks can be generated from images. Each image is represented as an undirected graph $G = (V,E)$, where $V$ is a set of vertices ($V = \{v_1, v_2, ..., v_n\}$) and $E$ is a set of edges ($E = \{e_1, e_2, ..., e_k\}$). Each vertex $v_i \in V$ corresponds to an individual pixel and similarity/closeness of pixels are modeled as edges: an edge $e_{ij} \in E$ connects vertices $v_i$ and $v_j$. The weight of each edge, $w_{ij}$, is a non-negative value that measures the affinity between $v_i$ and $v_j$. A higher affinity represents a stronger relation between corresponding pixels.

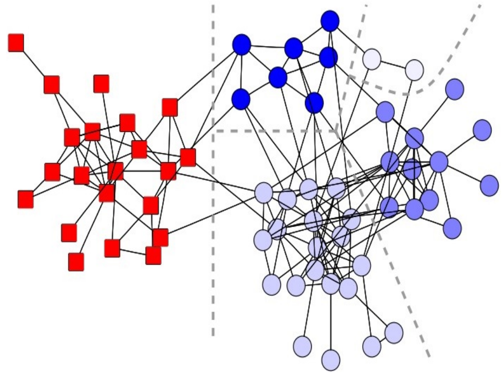

Figure 1: Community structure in the social network of bottle-nose dolphins population extracted using the algorithm of Girvan and Newman (Girvan and Newman, 2002). The squares and circles denote the primary split of the network into two groups and the circles are further subdivided into four smaller group as (Newman, 2004).

In this paper, edge weights are defined as:

$$w_{ij} = \begin{cases} 1 & if \quad d_{ij}^c \leq t \text{ for all color channels } c \\ nil & otherwise \end{cases} \tag{3}$$

where $t$ is a threshold, $d_{ij}^c$ is a measure of the similarity of pixels $i$ and $j$ intensity for color channel $c$ (among R, G and B). It is defined by $d_{ij}^c = \left| I_i^c - I_j^c \right|$ where $I_i^c$ and $I_j^c$ represent the intensity of pixel $i$ and $j$ respectively for channel $c$.

For a given pixel, links towards other pixels are created if and only if other considered pixels are inside 20 neighboring pixels for rows and columns directions. Plus all distances $d_{ij}^c$ of color channels must be lower than $t$ for the edge to be considered. In this case, the weight is assigned $w_{ij} = 1$. Empirically, the 20 value is based on several experiments that shows a relatively good performance with this value. Note that we could have put an edge and a weight that reflect the distance (both physical distance and color distance) in a more complex way but this is left for future investigations.

## 3.3 Louvain Algorithm

The Louvain method (Blondel et al., 2008) is a hierarchical greedy algorithm that is designed to optimize the modularity (see Equation 2) on graphs or weighted graphs.

Louvain algorithm is an iterative process that consists of two phases. Initially, every node is a singleton community. Next, during the first phase, all nodes are considered one by one. Each node is placed in its neighboring community, including its own one, that maximizes the static modularity gain. This process is repeated until no further improvement can be achieved and this first phase therefore stops when the modularity reaches a local maximum. Then, the second phase consists in building a new graph whose nodes are the communities found during the first phase. To build this graph, links between nodes of the same community lead to self-loops while the weights of links between new nodes are computed by the sum of the weights of the links between nodes in the corresponding two communities. The global process is illustrated in Figure 2.

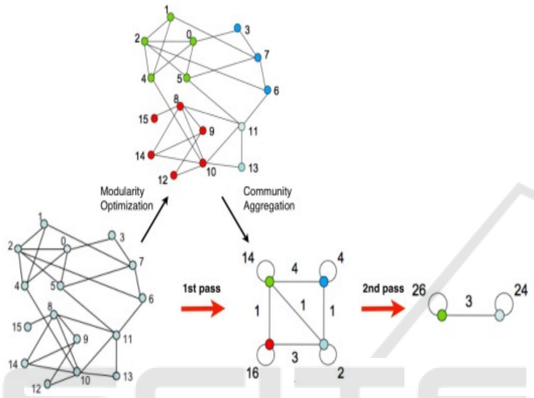


Figure 2: Process of community detection for Louvain method (Blondel et al., 2008). Each pass consists of two phases: modularity optimization using local movements and aggregation of communities.

### 3.4 Merging Homogeneous Regions Algorithm

Maximizing modularity is a NP-hard problem and community detection algorithms are generally heuristics algorithms (mostly without guarantee) and not exact ones. Furthermore, image segmentation based community detection often leads to over-segmentation (Nguyen et al., 2018b). In order to solve this problem, a solution is to combine homogeneous regions whenever possible (Nguyen et al., 2018a).

Given an over-segmented image that consists of a set of homogeneous regions. Let *regthres* is the threshold that defines the number of pixels in one small region, function $C(R_i)$ returns the number of pixel in region $R_i$ and *threshold(t)* is the similarity distance threshold. Our algorithm can merge these regions in order to generate better segmented image results. It is described as *Pseudocode* below:

**Algorithm MHR**

**Input:** A set of regions $R = \{R_1, R_2, ..., R_n\}$

**for** ($R_i \in R$) **do**
    **for** ($R_j \in R$; $i \neq j$) **do**
        **if** ($R_i$ and $R_j$ are adjacent regions)
            **if** (($C(R_i) < regthres$) *OR* ($C(R_j) < regthres$))
                Merge region $R_i$ and region $R_j$
            **else**
                Compute similarity distance $d(R_i,R_j)$
                **if** ($d(R_i,R_j) >= threshold(t)$)
                    Merge region $R_i$ and region $R_j$
                **end if**
            **end if**
        **end if**
    **end for**
**end for**

**Output:** The set of image segmentation result $R = \{R_1, R_2, ..., R_k\}$

## 4 IMPLEMENTATION AND PERFORMANCE

In this Section, we detail our implementation strategy and study the effects of various choices on performances.

### 4.1 Features for Similarity

In the algorithm MHR, the similarity between region $R_i$ and region $R_j$ is computed as using Equation 12 that we will detail below. The primary straightforward feature for image segmentation is color (Li and Wu, 2015; Mourchid et al., 2017) which is essential when segmenting images using community detection. However, the color feature alone cannot achieve good segmentation if the image is composed of repetitive patterns of different colors in many homogeneous objects. In the proposed algorithm, we incorporate the histogram of oriented gradients (HOG) and the color features into a so-called similarity feature vector that represents each region.

#### 4.1.1 The HOG Feature

The histogram of oriented gradients is computed based on a grayscale image: given a grayscale image I, we extract the gradient magnitude and orientation as using the 1D centered point discrete derivative mask (4), (5) in the horizontal and vertical directions to compute the gradient values.

$$D_X = \begin{bmatrix} -1 & 0 & 1 \end{bmatrix} \tag{4}$$

and

$$D_Y = \begin{bmatrix} -1 \\ 0 \\ 1 \end{bmatrix} \tag{5}$$

We obtain the x and y derivatives by used a convolution operation (6), (7).

$$I_X = I * D_X \tag{6}$$

and

$$I_Y = I * D_Y \tag{7}$$

In this paper, we decided to use the oriented gradient given by Equation 8 to build the similarity feature vectors.

$$\theta = \arctan \frac{I_Y}{I_X} \tag{8}$$

In the implementation, we use the function *atan2* that returns a value in the interval $(-\pi, \pi]$. The orientation of gradient at a pixel is $\theta = atan2(I_Y, I_X)$ radians. The angle degrees are transformed by $\alpha = \theta * 180/\pi$, that give values in the range (-180, 180] degrees. To shift into signed gradient we apply formula 9 and obtain the range of the gradient [0, 360). The orientation of gradient is put into 9 bins that represent 9 elements in the similarity feature vectors. For each region, we compute the HOG feature by the statistic of the percentage of oriented gradient bins.

$$\alpha = \begin{cases} \alpha, & if \quad \alpha \geq 0 \\ \alpha + 360, & if \quad \alpha < 0 \end{cases} \tag{9}$$

#### 4.1.2 The Color Feature

For the color feature, we consider color images (with RGB color space, but other color spaces could be used as the principle remains generic) on individually color channels. For each region, we compute Mean and Standard deviation for every channel of colors as formulas (10), (11) which contribute 6 elements in the similarity feature vectors.

$$Mean(R) = \frac{\sum_{i=1}^{n} C_i}{n} \tag{10}$$

$$SD(R) = \sqrt{\frac{\sum_{i=1}^{n} (C_i - Mean(R))^2}{n}} \tag{11}$$

where $C_i$ is the color value channel of pixel $i$ in image and $n$ is the number of pixels in the set $R$.

#### 4.1.3 The Similarity Feature Vectors

For every region, we build a similarity feature vector including 9 elements coming from the HOG features and 6 elements coming from the color features. The HOG features for a region is obtained by the computing of percentage of oriented gradient bins. The color features are obtained by the combination of three pairs of Mean and Standard deviation for every color channels. The similarity distance of two adjacent regions $R_i$ and $R_j$ is computed by cosine similarities of a pair of 15-dimensional vectors $a_i, a_j$ that represented to two considering regions ($a_i, a_j \in R^{15}$), as indicated in equation (12).

$$d(R_i, R_j) = Cosine(a_i, a_j) = \frac{a_i^{\intercal} a_j}{\|a_i\|.\|a_j\|} \tag{12}$$

### 4.2 Noise Removal

In the implementation, a primary technique that must be pointed out is the noise removal process. As mentioned above, the results obtained from Louvain processes consist of over-segmented results, which decrease the quality when evaluated. In this paper, we recommend applying a noise removal strategy that offers better results and obtains higher evaluation scores. The removing noise process is a crucial part of our algorithm because it merges the small regions that remain after Louvain process. Empirically, we tried different values to set the threshold $regthres = \{100, 200, ..., 600\}$ on our sample dataset (a part of BSDS500) and obtained some potential insights: it is stable in terms of PRI score when the threshold *regthres* is in the range $\{100, 200, 300\}$. Therefore, we set the threshold for small regions to be *regthres* = 200 pixels for testing and evaluating on datasets.

## 5 EXPERIMENTAL EVALUATION

This Section provides experiments that were performed to assess our algorithm. To evaluate the proposed model, we used three publicly available datasets for image segmentation: Berkeley Segmentation Data Set 300 *(BSDS300)* (Martin et al., 2001), Berkeley Segmentation Data Set 500 *(BSDS500)* (Arbelaez et al., 2011) and MSRC object Recognition Data Set *(MSRC)* (Shotton et al., 2006). Three widely used evaluation segmentation metrics: Variation of Information *(VI)* (Meila, 2005), Segmentation Covering *(SC)* (Arbelaez et al., 2009) and Probabilistic Rand Index *(PRI)* (Pantofaru and Hebert, 2005) have been applied to measure the accuracy of proposed algorithm. The qualitative and quantitative evaluation are presented below in Tables 1, 2 and 3.

### 5.1 Datasets

The Berkeley Segmentation Data Set 300 (BSDS300) has been built with the aim of providing an empirical basis for research on image segmentation and boundary detection. This dataset comprises 300 images, including 200 images for training and 100 images for validation. Each image has 481 x 321 pixels, which yields a graph of 154401 vertices. The BSDS300 also provides multiple ground-truth segmentation images that are manually generated by many human subjects. For every image, there are from 5 to 10 ground-truth segmentation maps.

The Berkeley Segmentation Data Set 500 (BSDS500) is an extension of BSDS300. This dataset comprises 500 images, including 200 images for training, 200 new testing images and 100 images for validation. Each image has 481 x 321 pixels and has in average 5 ground-truth segmentation maps. Supplying a benchmark for comparing different segmentation and boundary detection algorithms.

The Microsoft Research Cambridge Object Recognition Image Database (MSRC) contains a set of 591 natural images of size 320 x 213 with one ground-truth per image grouped into categories. Its intended use is research, in particular object recognition research.

### 5.2 Evaluation Metrics

In general, evaluation segmentation metrics have been used to evaluate different image segmentation algorithms in the literature. Some common one include Variation of Information *(VI)* (Meila, 2005), Segmentation Covering *(SC)* (Arbelaez et al., 2009) and Probabilistic Rand Index *(PRI)* (Pantofaru and Hebert, 2005). Especially, PRI brings exceedingly benefit of evaluation on BSDS300 and BSDS500 datasets which provide multiple ground-truth.

The Probabilistic Rand Index (PRI) (Pantofaru and Hebert, 2005) is a classical evaluation criterion for clustering. The PRI measures the probability that pair of pixels have consistent labels in the set of manual segmentation maps (ground-truth). Given a set of ground-truth segmentation images $\{S_k\}$, the Probabilistic Rand Index is defined as:

$$PRI(S_{test},\{S_k\}) = \frac{1}{T}\sum_{i<j}[c_{ij}p_{ij} + (1-c_{ij})(1-p_{ij})] \tag{13}$$

where $c_{ij}$ is the event that the algorithm gives the same label to pixels $i$ and $j$, and $p_{ij}$ corresponds to the probability of the pixels $i$ and $j$ having the same label, and is estimated by using sample mean of the corresponding Bernoulli distribution on the ground-truth dataset. $T$ is the total number of pixel pairs. The PRI values range in [0,1] in which a larger value likely indicates a greater similarity between these segmentation images.

The Variation of Information (VI) metric was introduced for the evaluation of clustering (Meila, 2005). It measures the distance between two clusterings in terms of the information difference between them. VI is defined by:

$$VI(C,C') = H(C) + H(C') - 2I(C,C') \tag{14}$$

where $H(C)$ and $H(C')$ are the entropy of segmentation image $C$ and ground-truth $C'$, respectively and $I(C,C')$ is the mutual information of two segmentation image $C$ and ground-truth image $C'$. Let segmentation image $C$ and ground-truth image $C'$ have N levels of gray and distributions are uniform, *i.e. PN=1/N*. The maximal values of entropies $H(C) = logN$ and $H(C') = logN$, and let mutual information $I(C,C')$ be equal to zero. Hence, the range of this metric is $[0, 2logN]$, and the smaller value is the better segmentation results.

The Segmentation Covering (SC) metric that measures averaged matching between proposed segment with a ground-truth labeling was introduced by Arbelaez *et al.* (Arbelaez et al., 2009). It is defined by:

$$SC(S,S_g) = \frac{1}{N}\sum_{R\in S}|R|.\max_{R'\in S_g} O(R,R') \tag{15}$$

where $N$ denotes the total number of pixels in the image and the *overlap* between two regions $R$ and $R'$, defined as:

$$O(R,R') = \frac{|R\cap R'|}{|R\cup R'|} \tag{16}$$

### 5.3 Results

For qualitative evaluations, we present some images of the segmentation results in Figure 3 and Figure 4, collected from the dataset BSDS300. Figure 5 and Figure 6 are the representations for MSRC dataset segmented image results. Finally, Figure 7 and Figure 8 displays some segmentation images of the dataset BSDS500. For these qualitative results, we can see that the proposed algorithm offers good results and produces sizable regions for all selected images. Our algorithm can aggregate homogeneous neighboring regions successfully even if pixels inside each region are dissimilar. Besides the success of our method, it remains a challenge for segmenting images whose colors contained are quite different in parts of an object

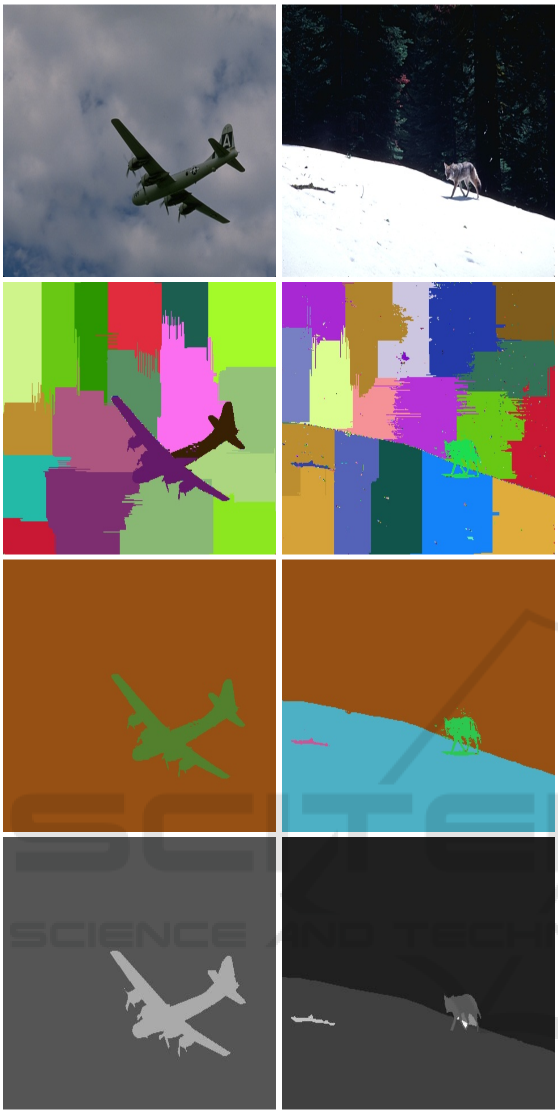

Figure 3: *Top:* Original images. *Second line:* Segmentation results obtained by the Louvain method. *Third line:* Segmentation results with the proposed algorithm. *Fourth line:* Ground-truth.

as we point out in Figure 9 and Figure 10. To solve this problem, we attempted to build a graph which encodes both texture and color features but is this left for future research.

From a quantitative point of view, we evaluated the segmentation results using evaluation metrics presented in section 5.2 (PRI, VI, SC) by comparing a test segmentation with multiple ground-truth images. We applied these evaluation metrics on the MSRC dataset, detailed results are given in Table 1. We run MHR algorithm on the validation set from the Berkeley segmentation data set 300 (BSDS300) and the test data set BSDS500, detailed results are given in Table 2 and Table 3, respectively.

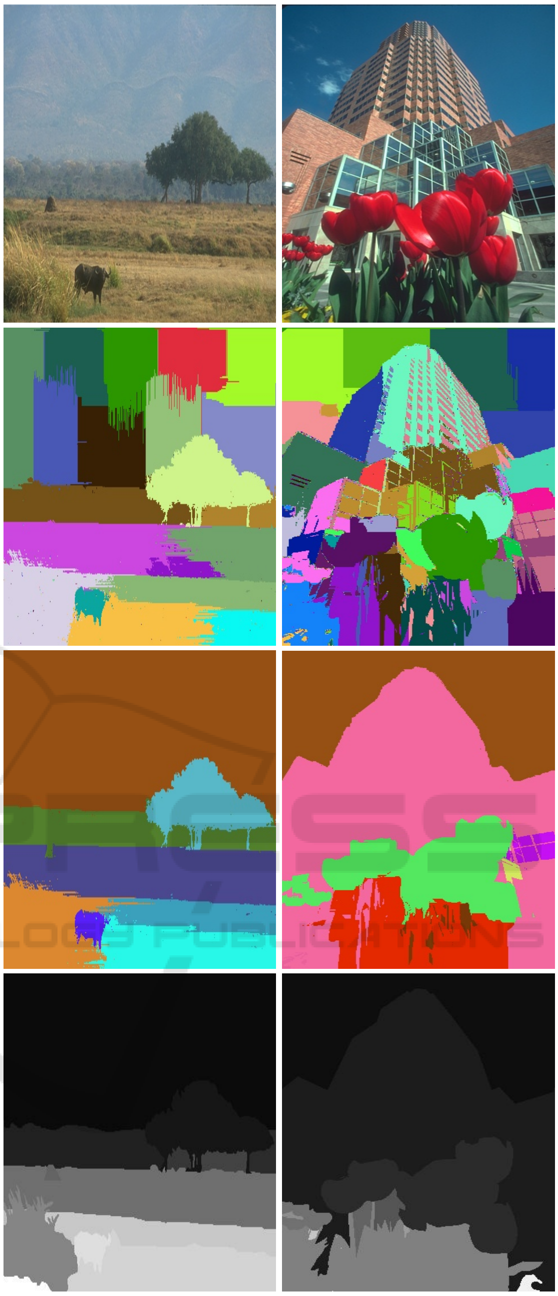

Figure 4: *Top:* Original images. *Second line:* Segmentation results obtained by the Louvain method. *Third line:* Segmentation results with the proposed algorithm. *Fourth line:* Ground-truth.

The evaluation results give the successful roof for our algorithm. Our method exceeds all previous graph-based algorithms in terms of PRI scores. Empirically, the threshold range for the agglomeration process is only taking range from 0.940 to 0.999 *(with 0.005 intervals)*. The best results are recorded when the value of cosine similarity distance equal to 0.995. Cosine similarity distance domain that offers best re-

Figure 5: *Top:* Original images. *Second line:* Segmentation results obtained by the Louvain method. *Third line:* Segmentation results with the proposed algorithm. *Fourth line:* Ground-truth.

Table 1: Quantitative comparisons on MSRC Object Recognition Data set using the proposed algorithm and gPb-owt-ucm and Canny-owt-ucm (Arbelaez et al., 2011).

| Methods | PRI | VI | SC |
|---|---|---|---|
| gPb-owt-ucm | - | - | 0.75 |
| **Our algorithm** | **0.74** | **1.36** | **0.75** |
| Canny-owt-ucm | - | - | 0.68 |

sults in our algorithm fall into [0.990, 0.999]. Note that the regions belong to one segment have HOG and color features properties in common to each other.

Table 2: Quantitative comparisons on BSDS300 validation set of the proposed algorithm and gPb-owt-ucm and Canny-owt-ucm (Arbelaez et al., 2011), Lv-ara (Nguyen et al., 2018a), HOG and FMS(HOG) (Mourchid et al., 2017), RGB(HoS) (Li and Wu, 2015), Lv-ahr (Nguyen et al., 2018b), Mean Shift (Comaniciu and Meer, 2002), NCuts (Cour et al., 2005), Felz-Hutt (Felzenszwalb and Huttenlocher, 2004).

| Methods | PRI | VI | SC |
|---|---|---|---|
| Human | 0.870 | 1.16 | - |
| **Our algorithm** | **0.822** | **1.399** | 0.74 |
| Lv-ara | 0.819 | - | - |
| Youssef Mourchild's *(FMS(HOG))* | 0.811 | - | - |
| gPb-owt-ucm | 0.810 | 1.47 | 0.75 |
| Youssef Mourchild's *(HOG))* | 0.803 | - | - |
| Lv-ahr | 0.80 | - | - |
| Mean Shift | 0.780 | 1.63 | 0.66 |
| Shijie Li's method *(L*a*b (HoS))* | 0.777 | 1.879 | - |
| Felz-Hutt | 0.770 | 1.79 | 0.68 |
| Canny-owt-ucm | 0.770 | 1.81 | 0.66 |
| NCuts | 0.750 | 1.84 | 0.66 |
| Shijie Li's method *(RGB (HoS))* | 0.749 | 2.149 | - |

Table 3: Quantitative comparisons on BSDS500 test set of the proposed algorithm and Pb-owt-ucm and Canny-owt-ucm (Arbelaez et al., 2011), Mean Shift (Comaniciu and Meer, 2002), NCuts (Cour et al., 2005), Felz-Hutt (Felzenszwalb and Huttenlocher, 2004).

| Methods | PRI | VI | SC |
|---|---|---|---|
| Human | 0.870 | 1.17 | - |
| **Our algorithm** | **0.835** | **1.30** | **0.74** |
| gPb-owt-ucm | 0.830 | 1.48 | 0.74 |
| Felz-Hutt | 0.800 | 1.87 | 0.69 |
| Mean Shift | 0.790 | 1.64 | 0.66 |
| Canny-owt-ucm | 0.790 | 1.89 | 0.66 |
| NCuts | 0.780 | 1.89 | 0.67 |

## 6 CONCLUSION

This paper proposes an efficient agglomerative algorithm cooperating with the Louvain method for community detection to implement image segmentation. Our method is significantly accurate and produces efficient image segmentation results. The novelty in this paper is the consideration of HOG and color features properties in order to build a 15-dimensional vector for each region and proposal to apply cosine similarity distance for aggregation processes. Our method does not need to recompute the feature properties when operated merging processes. Hence, the time complexity has been reduced significantly compared with the classical use of a 256-dimensional vector for each region and the recomputation of feature properties for every merging processes that is implemented in some other techniques. Extensive experiments have been performed, and the results show that the proposed algorithm can reliably segment the image and avoid over-segmentation in order to produce more accurate objects and enhance computing performance efficiently.

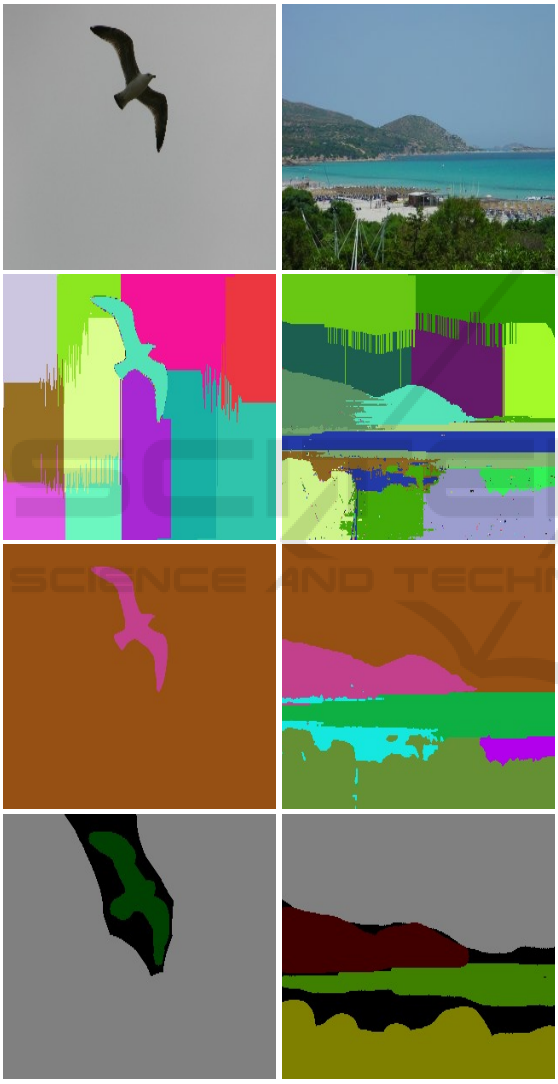

Figure 6: *Top:* Original images. *Second line:* Segmentation results obtained by the Louvain method. *Third line:* Segmentation results with the proposed algorithm. *Fourth line:* Ground-truth.

Figure 7: *Top:* Original images. *Second line:* Segmentation results obtained by the Louvain method. *Third line:* Segmentation results with the proposed algorithm. *Fourth line:* Ground-truth.

Figure 8: *Top:* Original images. *Second line:* Segmentation results obtained by the Louvain method. *Third line:* Segmentation results with the proposed algorithm. *Fourth line:* Ground-truth.

Figure 9: *Top:* Original images. *Second line:* Segmentation results obtained by the Louvain method. *Third line:* Segmentation results with the proposed algorithm. *Fourth line:* Ground-truth.

Figure 10: *Top:* Original images. *Second line:* Segmentation results obtained by the Louvain method. *Third line:* Segmentation results with the proposed algorithm. *Fourth line:* Ground-truth.

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