A New Image Segmentation Algorithm: A Community Detection Approach

Ahmad Ali Abin, Farzaneh Mahdisoltani, and Hamid Beigy

Department of Computer Engineering, Sharif University of Technology, Tehran, Iran
{abin,mahdisoltani}@ce.sharif.edu
{beigy}@sharif.edu

Abstract. The goal of image segmentation is to find regions that represent objects or meaningful parts of objects. In this paper a new method is presented for color image segmentation which involves the ideas used for community detection in social networks. In the proposed method an initial segmentation is applied to partition input image into small homogeneous regions. Then a weighted network is constructed from the regions, and a community detection algorithm is applied to it. The detected communities represent segments of the image. A remarkable feature of the method is the ability to segments the image automatically by optimizing the modularity value in the constructed network. The performance of the proposed algorithm is evaluated on Berkeley Segmentation Database and compared with some well known methods. The results show that the proposed algorithm performs better than the other known algorithms in terms of qualitative accuracy. The proposed algorithm being simple and easy to implement, is well suited for fast processing applications.

Keywords: Color Image, Image segmentation, Complex networks, Community structure, Community detection

1 Introduction

Image segmentation is defined as clustering pixels into salient image regions, i.e., regions corresponding to individual surfaces, objects, or natural parts of objects. Image segmentation could be used for object recognition, content-based image and video retrieval, video indexing, occlusion boundary estimation within motion or stereo systems, image compression. In [20], image segmentation is defined as the process of dividing an image into different regions such that each region is homogeneous, but the union of any two given adjacent regions is not [20].

A variety of algorithms have been proposed in the literature for segmentation purposes. In [28] the existing image segmentation algorithms are classified into three major categories: feature-space-based clustering, spatial segmentation, and graph-based approaches. In feature-space-based clustering approaches, image features, which are usually based on color or texture are used [15, 14]. A specific distance measure that ignores the spatial information is used to group the feature samples into compact, but well-separated clusters. Data clustering approaches are used in finding image features.

The spatial segmentation methods gather similar pixels according to some homogeneity criteria [5]. They are based on the assumption that pixels, which belong to the same homogeneous region, are more alike than pixels from different regions. The split-and-merge and region growing techniques are examples of such methods[4].

Graph-based approaches are based on the combination of features and spatial information. In these approaches, grouping is based on factors such as similarity and continuation. The common idea among all these approaches is the formation of a weighted graph, where each vertex corresponds to an image pixel or a region, and the weight of each edge connecting two vertices represents the likelihood that they belong to the same segment. The constructed graph is partitioned into multiple components which minimize some cost function of the vertices in the components or the boundaries between them [26, 16].

Other than the mentioned categories, hybrid approaches have emerged. Many of these hybrid techniques combine region-based methods with feature-based ones. These algorithms for segmentation are popular because they rely on both global and local information. The watershed algorithm [24] is an example of these hybrid algorithms. It begins by using a feature-based method to calculate the gradient magnitude and produces regions by a region-growing technique.

In this paper, the idea of community detection in social networks is used to segment an image. Firstly, an initial segmentation is applied in order to partition the input image into small homogeneous regions. Then a weighted network is constructed from the regions, and a community detection algorithm is applied to it. The detected communities represent segments of the image, which are extracted via a community detection approach.

The rest of this paper is organized as follows. Section 2 reviews some concepts related to community detection in complex networks. The proposed segmentation algorithm is presented in Section 3. Experimental results are given in Section 4. Finally, concluding remarks are given in Section 5.

2 Community Detection

Some related concepts of community detection are described in this section. The study on networks has become one of the most interesting topics nowadays. Community structure, which is a property of complex networks, can be described as the gathering of vertices into groups such that there is a higher density of edges within groups than between them [8]. A network with community structure is shown in Fig. 1. Each dashed circle represents a community with dense internal links while exhibiting few external links [19]. Many methods and algorithms have been proposed so far to extract the community structure in networks. The success of an algorithm in finding communities depends on the definition of community it uses. Many definitions of community are given in [27]. Girvan and Newman [19] have defined network modularity Q, a quantitative metric which is widely

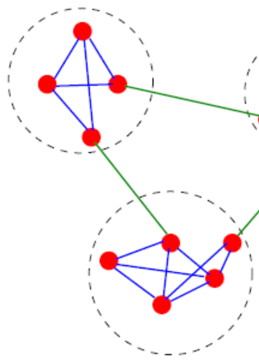

Fig. 1. A small network with community structure [12].

used for evaluating a partitioning of a network into communities as below:

$$Q = \sum_i (e_{ii} - a_i^2), \tag{1}$$

where i is the index of the communities, e_{ii} is the ratio of inter-community links to the total number of links in the network, and a_i is the ratio of all links having at least one node in the community i to the total number of links in the network. Most recent algorithms use network modularity as a quality metric for detecting communities, such as Newman-Fast algorithm [19], the algorithm for very large networks [8], and the algorithm using Extremal Optimization [11].

In this paper the Newman-Fast algorithm is used as the community detection algorithm. It works by optimizing the network modularity Q, [19] of a simple undirected network. The measure Q is calculated from (1). In other words, Q is the total fraction of links which have both ends in the same cluster subtracted from the same value in an equivalent random graph. The equivalent random graph of a desired graph is one with same vertices while the links are placed randomly. Basically, Q estimates how meaningful a partitioning of a network is. A high value of Q indicates a good partition of the vertices [1]. The Newman-Fast algorithm is based on a greedy approach to maximize Q. Each individual vertex is assumed as a community at first and then, Newman-Fast finds a pair of communities whose merging gives the maximum increase in Q repeatedly until the original graph is built. The algorithm outputs the community division with the highest modularity value finally.

In particular, the possible pairs of regions to join are determined as the set of community pairs with at least one inter-community link in the original graph. The change in the value of Q imposed by joining clusters V_i and V_j is given in (2).

$$\Delta Q_{ij} = e_{ji} + e_{ji} - 2a_i a_j. \tag{2}$$

After calculating all the differences of Q for possible joins, the clusters with the highest difference of Q are joined. This process continues until only one cluster remains.

3 The Proposed Segmentation Method

The proposed segmentation method is as follow. Firstly, an initial segmentation is applied to the input image in order to segment it into small homogeneous regions. Then a weighted network is constructed from these regions and a community detection algorithm is applied to it to extract the communities of the network. Each achieved communities represents a segment in the original image. Fig. 2 illustrates the structure of the proposed method. The details of each process are described below.

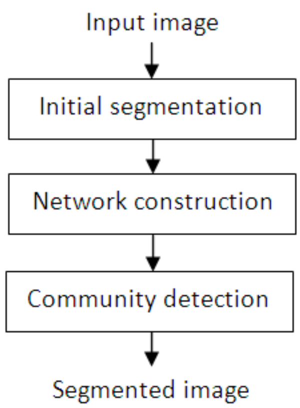

Fig. 2. Structure of proposed method.

3.1 Initial Segmentation

The initial segmentation, partitions the image into homogeneous, possibly small regions which are used in the next step to build the network. Any existing segmentation method, such as JSEG [10], super-pixel [21], meanshift [6, 9], watershed [25] and levelset [23], can be used in this step. In this paper, the JSEG is chosen as the initial segmentation to segment the input image into small enough segments initially. Fig. 3 shows the result of JSEG segmentation on some typical images.

(a) (b)

Fig. 3. (a) A typical color image, (b) JSEG initial segmentation result on (a).

3.2 Constructing the network

In this step, we construct a network from the regions which exhibits community structure. The model is defined by the following steps:

1. Firstly, each region is separated solely into a vertex. There are a total of M vertices in the network where M is the number of regions.

2. Every pair of vertices are connected through an edge. In other words, we have a clique.

3. Starting from the M vertices, we calculate the similarity between all pairs of regions. The RGB color space is used to compute the color histogram. Each color channel is uniformly quantized into K levels and then the histogram of each region is calculated in the feature space of $K \times K \times K = K^3$ bins. We used the Bhattacharyya coefficient [2], $S(R, Q)$, as the similarity measure between regions R and Q which is defined as (3).

$$S(R, Q) = \sum_{u=1}^{K^3} \sqrt{H_R^u . H_Q^u}, \tag{3}$$

   where H_R and H_Q are the normalized histograms of R and Q respectively and the superscript u represents the uth element of them. Bhattacharyya coefficient is actually the cosine of the angle between the vectors

$$\left(\sqrt{H_R^1}, ..., \sqrt{H_R^{K^3}}\right)^T and \left(\sqrt{H_Q^1}, ..., \sqrt{H_Q^{K^3}}\right)^T.$$

   If two regions have similar contents, their histograms will be similar, and hence their Bhattacharyya coefficient will be high. In other words, higher Bhattacharyya coefficient means higher similarity.

4. This part of our method is related to assigning weights to the edges of the network, regarding the possibility of utilizing Newman-Fast algorithm for weighted networks which is mentioned in [19]. For this purpose, we normalize the Bhattacharyya similarity measure between regions v_1 and v_2 as (4) and assign it to the corresponding edge.

$$W(v_1, v_2) = \frac{exp(-\frac{1}{S(v_1,v_2)})}{\sum_{i \neq j \in R} exp(-\frac{1}{S(v_i,v_j)})}, \tag{4}$$

where R is set of all regions.

3.3 Extracting communities from the network

After the creation of the network, the weighted Newman-Fast community detection algorithm is applied to the network to extract the communities. Also

any existing community detection algorithm such as Minimum-cut method [18], Girvan-Newman algorithm [13], the Louvain method [3] can be used instead of the Newman-Fast algorithm to extract the communities.
Each community consists of vertices corresponding to regions which are similar to each other and dissimilar to the regions in other communities. Therefore, each extracted community represents a segment in the input image.
As mentioned in section 2, the Newman-Fast algorithm optimizes the modularity measure Q of a simple undirected network. The measure Q estimates how meaningful a particular partitioning of the vertices in a network is. Basically, a high value of Q indicates a good partitioning of the vertices. The Newman-Fast algorithm engages a greedy approach to maximize Q. It initially assumes each vertex as a community, and repeatedly finds the pair of communities whose joining leads to the greatest increase in Q. It continues to join the communities until the original graph is formed. Finally, the community division with the highest modularity value is chosen as the output. In the method given in this paper, the constructed network is fed to the Newman-Fast algorithm and the partitioning of it with highest modularity value is considered as the segmentation result. Fig. 4 shows a typical image and the change of Q in community detection algorithms along with the segmentation result. As shown in Fig. 4, the Newman-Fast algorithm reaches the highest value of Q where the number of communities equals to 4.

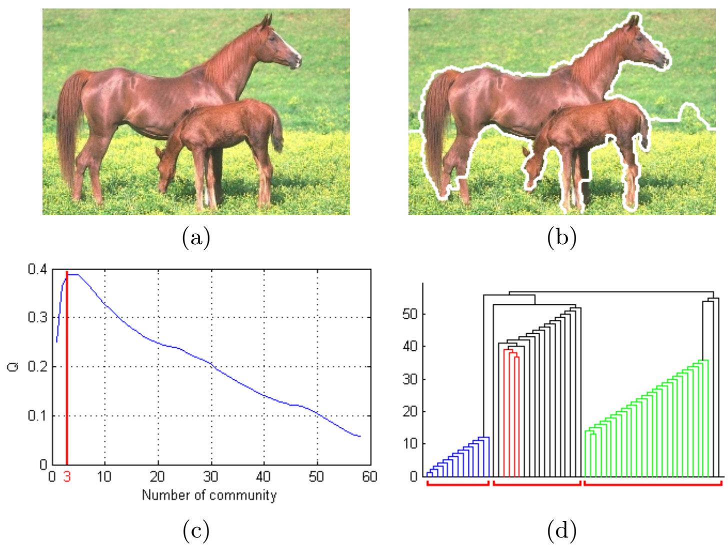

Fig. 4. (a) A typical color image, (b) The final segmentation result, (c) The plot of modularity value Q, (d) The resultant Dendrogram.

The whole algorithm can be summarized as follows:

Input: The initial segmentation result.
Stage 1: Perform the initial segmentation.
    Set R={the set of regions obtained from initial segmentation}
Stage 2: Network construction
    For each region I in R
        Assign vertex V_I in the graph to I
    End for
    For each region I in R
        For each region J in R and $I \neq J$
            Set $S(I, J)$=Similarity between I and J
            Set $S'(I, J)$=The normalized $S(I, J)$ using equation 4
            Set weights of $W(V_I, V_J) = S'(I, J)$
        End for
    End for
Stage 3: Community extraction
    3.1. Separate each vertex solely into a community.
    3.2. Calculate the increase of Q for all possible community pairs.
    3.3. Choose the mergence of the greatest increase in Q.
    3.4. Repeat 3.2 and 3.3 until the modularity Q reaches the maximal value.
Stage 4: Return each extracted community as a segment.

4 Experimental Results

We have performed our experiments successfully using the proposed segmentation algorithm on images selected from Berkeley segmentation dataset (BSDS) [17]. Fig. 5 illustrates some of our results. We have obtained reasonably good results. We have also performed comparisons with some existing segmentation algorithms. The method is carried out on a 2 GHz processor with 1024 MB RAM on Windows XP professional platform. MATLAB 7.1 and image processing toolbox 5.0.2 are used. The quantization level, K, is set to 16 in the network construction step. The results are compared with three segmentators JSEG [10], EDISON [7] and MULTISCALE [22]. These segmentation methods are well known and often used for image segmentation. Most of these methods have several control parameters. Some parameters specify image size or output format. Other parameters are essential to the segmentation process. The JSEG algorithm parameters are set to the default values for segmentation. The minimum region size in EDISON segmentator is set to 1000 and the other parameters have the same values that the authors used as default in [7]. In [22], some parameters are recommended as "safe". These values have been taken at testing for MULTISCALE segmentator.

Fig. 5 shows the final results of the proposed method with JSEG being used as initial segmentation algorithm. As the Fig. shows, the algorithm segments the output of the JSEG such that a viewer will perceive it as a well segmented image subjectively.

In Fig. 6 the result of the proposed method is compared to the 3 mentioned methods. Here, it can be observed that the proposed method has achieved much better results than other methods subjectively and in many cases, separates the main object of the image correctly. This characteristic which many other methods miss, has emerged in our proposed method.

As the results indicate, the superiority of the proposed method over other methods. But as stated before, our proposed method uses only the color histogram data as a measure of similarity. So it is unlikely for the approach to operate properly where color similarity is high between the regions belonging to segments with different textures. However, other segmentation methods often encounter problem in such cases and are not able to carry out the task properly and use the texture information between different regions to overcome this problem. The results of the Proposed method for two images was shown in the Fig. 7. As can be seen, the proposed method failed to segment the desired object properly. The reason is the high similarity among the object and the background in color image. Hence, incorporating the texture information can be considered as a good candidate to handle such cases.

5 Conclusions

This paper proposed a novel approach for image segmentation which is based on community detection algorithms existing in social networks. The JSEG segmentation algorithm segments the image into small regions firstly. The novelty in this paper is the consideration of the initially segmented image as a weighted network. Since the regions belonging to one segment have high similarity to each other, a community detection algorithm can be used to extract the communities from the network which actually represent the segments. Extensive experiments have been performed, and the results show that the proposed scheme can reliably segment the input color image so that the subject evaluates it as well segmented. It is worth mentioning the independence of the algorithm from the initial segmentation method whereas [10, 25] can be used instead of JSEG. In the future, we will explore how to incorporate the texture information to form the weighted network and enhance the results.

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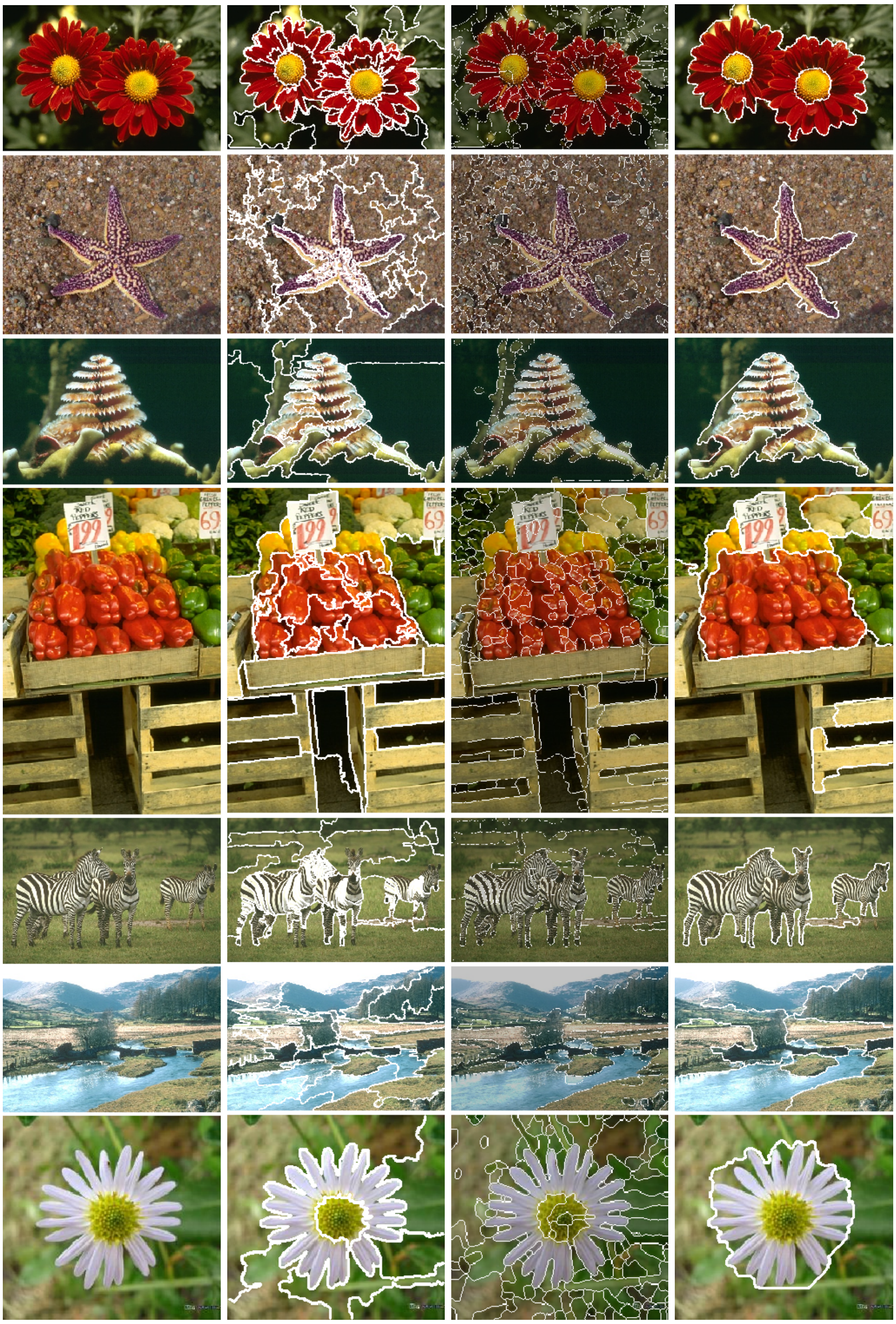
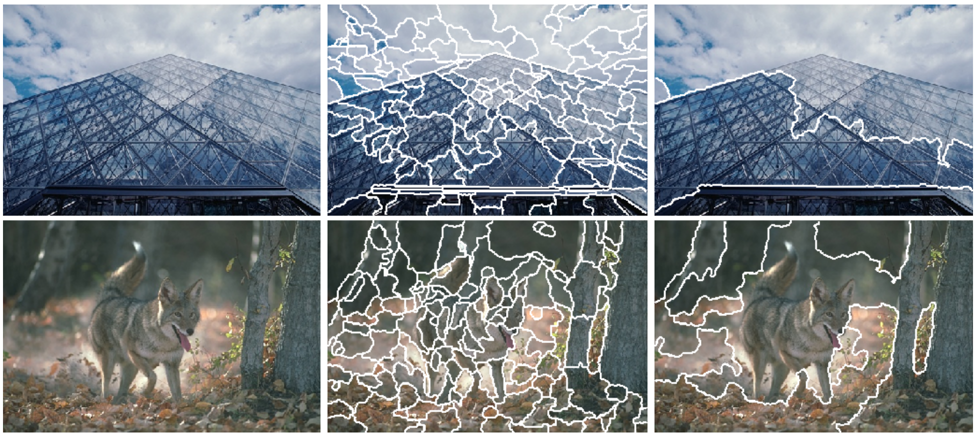
(a) (b) (c)

Fig. 5. (a) The input image, (b) The initial JSEG segmentation on input image, (b) Final result.



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

Fig. 6. (a) Input image, (b) EDISON, (c) MULTISCALE, (d) Proposed method.



(a) (b) (c)

Fig. 7. (a) Input image, (b) Initial segmentation with JSEG, (c) Final result.

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