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Sequential image segmentation based on minimum spanning tree representation☆

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ABSTRACT

Image segmentation is a very important stage in various image processing applications. Segmentation of pixels of an image and clustering of data are closely related to each other. For many graph-based data-clustering methods and many graph-based image-segmentation methods, minimum spanning tree (MST)-based approaches play a crucial role because of their ease of operation and low computational complexity. In this paper, we improve a successful data-clustering algorithm that uses Prim's sequential representation of MST, for the purpose of image segmentation. The algorithm runs by scanning the complete MST structure of the entire image, such that it finds, and then cuts, inconsistent edges among a constantly changing juxtaposed edge string whose elements are obtained from the MST at a specific length. In our method, the length of the string not only determines the edges to compare, but also helps to remove the small, undesired cluster particles. We also develop a new predicate for the cutting criterion. The criterion takes into account several local and global features that differ from image to image. We test our algorithm on a database that consists of real images. The results show that the proposed method can compete with the most popular image segmentation algorithms in terms of low execution time.

1. Introduction

Image segmentation is an image clustering problem; it is one of the most important and difficult computer vision and pattern recognition problems. This problem includes the process of dividing an image into homogeneous regions or segments such that the homogeneity can be measured based on the similarity of the properties of the image, such as the gray level, color, or texture [1–3]. Using the texture features of the image has a high computation complexity [4]. On the other hand, grayscale images inherently supply less information than color images [5]. Therefore, in many computer vision and pattern recognition applications, color image processing is more popular because of its practicality and accuracy [6]. In color image processing, appropriate color spaces and metrics can be used to measure similarities [5]. To perform the segmentation process, certain algorithms use global information extracted from the entire image, whereas other only use local information obtained from within the image. Many methods that use global information take a long time, whereas those that use only local information take a short time, but are usually misdirected by noise [7].

Clustering is an unsupervised process that categorizes data into groups, as in the image segmentation process [8]. According to Wertheimer's gestalt theory [9], image segmentation has a close relationship with data clustering as a perceptual process [10]. Therefore, in the following sections, both (indeed, simultaneous) data clustering and image segmentation are of interest.

In graph-based approaches to image segmentation, an image is mapped onto a plane using graph theory tools [11]. Graph theory helps to obtain information about the properties of the image. Graph-based image segmentation groups and organizes feature information and spatial information [3]. In addition to feature similarity, graph-based clustering approaches also take into account the connectivity and structural similarity of vertices (or nodes), which indicate pixels in the image [12,13]. After mapping the image onto a graph, the segmentation process is performed in a discrete connectivity space; thus, graph-based segmentation or clustering methods do not require discretization and do not produce any discretization error [10]. Because of the effective and powerful data representation (in addition to other advantages), the graph-based approach has been employed in many popular image segmentation and data clustering methods [7,13–18].

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In graph-based color image processing, pixels can be assumed to be vertices, and images with a size of A pixels in height and B pixels in width can be assumed to be an $A \times B$ vertex array. Each pixel has a color value vector in a color space (e.g., RGB). An edge is a link that connects the two vertices; in a weighted graph, each edge has a quantitative cost, which can be represented (for example) as the color difference between two adjacent vertices in the image graphs, such that it can be set using a distance measurement such as the Euclidean distance in the color space [5,7]. In graph-based image processing, vertices are connected to each other via a certain number of neighbors, such as in 8-neighboring or 8-connected vertices [2,7].

A spanning tree is a weighted, undirected, and acyclic subgraph. If there is only one path between all the pairs of vertices in a graph (i.e., there are no cycles or loops in the graph), the graph is acyclic. If each edge has an assigned orientation to another edge in a graph, the graph is a directed graph; otherwise, the graph is an undirected graph. A minimum spanning tree (MST) or a shortest spanning tree (SST) is a spanning tree with the least total weight of all edges among the all possible spanning trees [2,11,19]. The most popular MST extracting algorithms are Boruvka's algorithm [20], Kruskal's algorithm [21], and Prim's algorithm [22]. Boruvka's algorithm forms the MST by finding the nearest vertex for each vertex, and then, the nearest vertex for each tree, and merges them hierarchically such that no cycle is formed. Kruskal's algorithm forms the MST by listing all of the edges in ascending order and adding to the MST at the lowest priority, without generating any cycles. Prim's algorithm forms the MST by finding the nearest edge to the tree that has been formed by beginning from an arbitrary vertex and adding to the tree, such that the edge to be added will not form a cycle.

Many graph-based clustering algorithms and graph-based image-segmentation algorithms have widely used MST structures and algorithms because of their high performance, ease of retention of data and clusters, and ease of operation. The most popular MST-based clustering and segmentation algorithms will be presented in the next chapter. Our method is inspired by a clustering algorithm proposed by Wang et al. that is a recent MST-based clustering algorithm [23]. To operate the algorithm, first, Prim's algorithm is run to extract the MST that spans all of the data. Prim's algorithm adds one edge to the MST structure being formed at each cycle and into a one-dimensional edge list at the same time. After obtaining the MST, the clustering algorithm composes an edge list from the added edges in the order of their addition. Finally, an edge string consisting of edges from the list, the length of which is determined previously by users, is taken forward through the list; during this process, the edge at the exact center of the string is cut if it is the maximum weighted edge among the edges in the string. Although the algorithm gives quite good results for data clustering, when it is directly applied to image segmentation, it fails, unlike other segmentation algorithms. Adapting this method to different images using only the length of the string is very difficult, because, there is no adaptive threshold value that varies according to the characteristics of the given image. The time complexity of the algorithm is in a good quality [23].

In the proposed algorithm, we present a new predicate as a cutting criterion. Instead of the entire frame, we separately consider both sides of the center of the frame and use a threshold value for adaptation. The threshold value can be manually determined by the user to control the segmentation or automatically determined using the method presented in this paper. Moreover, we reduce noise segments using the given parameter for the length of the edge string. In this paper, we apply the algorithm to real images from the Berkeley Image Segmentation Dataset [24]. Our experimental results show that our method is able to compete with the most popular image segmentation algorithms.

2. Releated works

Image segmentation and clustering is a very challenging problem. No method among the clustering and segmentation methods achieves complete success. Several perform well, but take a very long time. Others are fast, but cannot prevent noise. Moreover, no single successful method is suitable for all data. In this section, we briefly mention some of the studies that are relevant to data clustering and image segmentation, i.e., those that use the MST structure. These studies have a long history.

In 1969, Gower and Rose [25] presented two iterative algorithms which are both called MST-based single linkage clustering. These methods are more practical than traditional clustering methods up to that time, because they use an algorithm that finds the MST, and thus, the results are obtained in a short computing time. Both methods perform clustering using a threshold value on the MST of data. Zhan [13] proposed an MST-based method that is based on the global properties of data. This method calculates a different threshold value for each edge using the standard deviations and means of the connected vertices at the ends of the edge, and a constant value. If the weight of the edge is larger than the threshold, the edge is cut.

Morris et al. [2] proposed a recursive MST-based image segmentation method called recursive SST segmentation. This method uses Kruskal's algorithm. Initially, each vertex defines a region. The two adjacent regions at the end of the smallest edge are merged. Then, the merged regions are combined into the same region, and the values of the vertices in the new region are altered based on the mean of the new region. Thus, new weights of the edges are updated according to the new region value. There should be one shortest edge between each adjacent region. In each cycle, the processes are repeated until the desired cluster number is reached.

Xu and Uberbacher [7] proposed an MST-based image segmentation method on greyscale images using Euclidean distances. This method tries to create homogenous regions by minimizing the sum of variations of all regions. To achieve this goal, each subtree should have greater than or equal to a specified number of vertices. Additionally, neighboring subtrees should be noticeably different from each other.

Xu et al. [17] developed three clustering algorithms using Euclidean distance. The first algorithm simply partitions the MST of the data by cutting the $k-1$ longest edge for k cluster. The second algorithm iteratively partitions the MST by decreasing the total difference between each vertex and the mean value of the cluster in which the vertices exist; the method uses an objective function to perform this task. The third algorithm finds the globally optimal solution to the clustering problem. This method selects k representative vertices based on minimization of the total weight between the each vertex and its closest representative vertices. Similarly, the method also uses a slightly differently objective function from previous one. Olman et al. [26] present a one-dimensional clustering approach that is useful for our method. According to the approach, a clustering problem is transformed to a string-partitioning problem using Prim's sequential MST representation.

Felzenszwalb and Huttenlocher [15] define a predicate for measuring the evidence between neighboring regions. The method uses not only local information, but also global information regarding the regions, such as cluster size and longest edge for each cluster. However, this method generates many small segment particles in the segmentation result. This method requires another process to eliminate the particles. Haxhimusa and Kropatsch [18] present a hierarchical partitioning method using Boruvka's algorithm and benefiting from the homogeneity criterion of [15].

Grygorash et al. [27] proposed two methods, one takes into account the given value for the number of clusters, and the other takes into account a threshold value. These methods are similar to