

A Review on Graph Based Segmentation

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Abstract— A graph implement the graph and hypergraph concepts from mathematics so that graph is an abstract data type. Effective understanding of digital images can be obtained from image segmentation. Past few decades saw hundreds of research contributions their vast research in the image segmentation field. However, the research on the existence of general purpose segmentation algorithm that suits for variety of applications is still very much active. The review is done based on the classification of various segmentation techniques within the framework of graph based approaches.

Index Terms— Image segmentation, graph based method, graph partition method, image analysis

I. INTRODUCTION

A graph data structure consists of a finite (and possibly mutable) set of ordered pairs, called edges or arcs, of certain entities called nodes or vertices. The nodes may be part of the graph structure, or may be external entities represented by integer indices or references. A graph data structure may also associate to each edge some edge value, such as a symbolic label or a numeric attribute (cost, capacity, length, etc.). In graph theory, a cut is a partition of the vertices of a graph into two disjoint subsets. The cut-set of the cut is the set of edges whose end points are in different subsets of the partition. Edges are said to be crossing the cut if they are in its cut-set. Graph can be of Weighted graph and unweighted graph. In an unweighted undirected graph, the size or weight of a cut is the number of edges crossing the cut. In a weighted graph, the same term is defined by the sum of the weights of the edges crossing the cut.

II. GRAPH CUT BASED METHOD

In the undirected, weighted graph $G=(V,E)$. Remove a subset of edges to partition the graph into two disjoint sets of vertices A,B (two sub graphs [1]).

Let s and t be two of the vertices in V , called the source and the sink respectively. Then, $V=M \cup \{s,t\}$. Each vertex in M is connected to all neighboring vertices in M by a bi-directional edge called an n -link (neighbor link). Each cut corresponds to some cost (cuts) as some of the weights for the edges that have been removed.

Each vertex in M is also connected to each of the terminals by uni-directional edges called t -links (terminal links). One set of t -links goes from the source vertex to all vertices in M , and one set of t -links goes from all vertices in M to the sink. In a weighted graph, each edge has a non-negative weight, also called a capacity.

To segment an image, each pixel in the image has its own vertex. These vertices form the group of vertices M . Each vertex in M is connected to each neighboring vertex by an n -link. The neighborhood of a vertex is based on the neighborhood of that vertex's corresponding pixel. Each vertex in M can be connected to either four neighbors or eight neighbors, depending on the connectedness of the graph. Each vertex in M is then connected to both the source and sink vertices via t -links. An example of a two dimensional image graph of this type can be seen in Fig. 1.

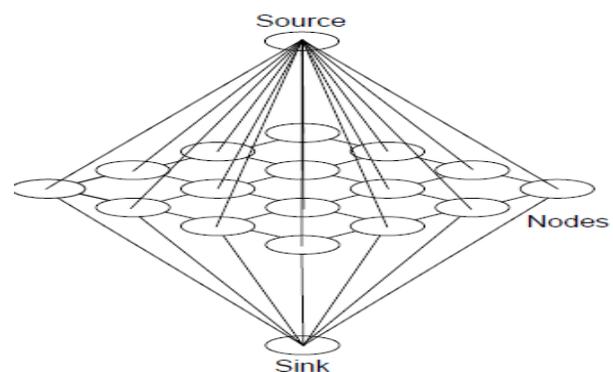


Fig. 1: An example of a 4x4 graph.

Greig [2] started the work on graph cuts [3,4,5]. Wu and Leahy [7] proposed a clustering method based on this minimum cut criterion. In particular, they seek to partition a graph into k -subgraphs such that the maximum cut across the subgroups is minimized. As shown in Wu and Leahy's work, this globally optimal criterion can be used to produce good segmentation on some of the images. However, as Wu and Leahy also noticed in their work, the minimum cut

criteria favors cutting small sets of isolated nodes in the graph. This is not surprising since the cut increases with the number of edges going across the two partitioned parts. Fig. 2 illustrates one such case.

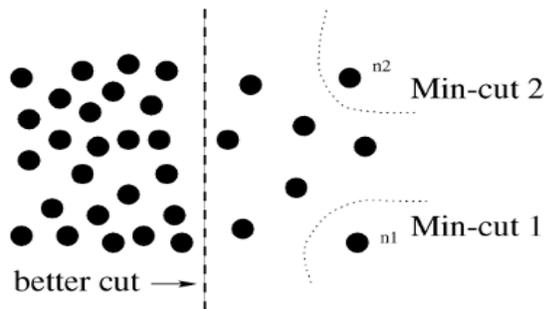


Fig. 2. A case where minimum cut gives a bad partition.

In optimization theory, the max-flow min-cut[8,9] theorem states that in a flow network, the maximum amount of flow passing from the source to the sink is equal to the minimum capacity that when removed in a specific way from the network causes the situation that no flow can pass from the source to the sink. The max-flow min-cut[8,9] theorem is a special case of the duality theorem for linear programs and can be used to derive Menger's theorem and the König-Egerváry Theorem. One of the oldest algorithms for dividing networks into parts is the minimum-cut method (and variants such as ratio cut and normalized cut[10]). In the minimum-cut method, the network is divided into a predetermined number of parts, usually of approximately the same size, chosen such that the number of edges between groups is minimized. Let us use an example involving water running from a source, through a network of pipes (edges), to a drain (a sink). We want to increase the amount of water running through those pipes until there is a bottleneck somewhere that stops us from increasing the amount of water. We have to search through the system of pipes looking for a path that goes all the way from the source to the sink where all pipes in the path have some space left to push more water through (positive residual capacity). If we cannot find a path from the source to the sink that has a positive residual capacity through all the pipes in the path, that means that there is a bottleneck, and we cannot increase the flow any more. If the flow cannot be increased, that means that the maximum flow has been found. When creating the graph, both bi-directional edges and uni-directional edges are created using two edges. For a bi-directional edge, each edge simply has the same capacity. Thus, flow can go in either direction. For a uni-directional edge, one edge has a positive capacity, and the other edge has a capacity of zero. This way, flow can only go in one direction. However, an edge with capacity zero and negative flow has a positive residual capacity. This means that

running flow through an augmenting path can lessen the flow through a uni-directional edge.

A search for an augmenting path is run on the graph. When an augmenting path is found, the following steps take place.

1. The minimum residual capacity along the path is found.
2. Flow equal to the minimum residual capacity along the network is added to every edge in the path.
3. Flow equal to the minimum residual capacity along the network is subtracted from the reverse of every edge in the path.

III. GRAPH PARTITION METHOD

Graph partitioning is a hard problem, practical solutions are based on heuristics. Local and global are the two broad categories of methods of graph partitioning. Kernighan–Lin algorithm[11], and Fiduccia-Mattheyses algorithms[12] are the well known local methods in which were the first effective 2-way cuts by local search strategies. Their major drawback is the arbitrary initial partitioning of the vertex set, which can affect the final solution quality. Global approaches rely on properties of the entire graph and do not rely on an arbitrary initial partition. The most common example is spectral partitioning, where a partition is derived from the spectrum of the adjacency matrix. Image segmentation produces a set of homogeneous regions of an image such that all pixels of a region are desired to be connected. The integration of all these regions constitutes the entire image. Each region has a set of pixels and each pixel is characterized by its position and feature vector. All pixels of a region are similar with respect to a set of features. The basic principle of most of the graph based segmentation methods is graph partitioning. Each method treats an image as a graph G in which vertices are composed of pixels. Each edge has a weight generally determined based on the vertices it relates. In graph theory sense, the above segmentation concept is similar to finding a set of sub-graphs $(SG_1, SG_2, \dots, SG_n)$ from the graph G such that for all $k \in (1, 2, \dots, n)$, $\forall i, j$ and $i \neq j$, $v_i, v_j \in SG_k$ with walks between v_i and v_j . The compounding of all the vertices of all the sub-graphs equals the complete set of vertices of the graph. Every sub-graph comprises of a collection of vertices with strong affinities among them. A pictorial representation demonstrating this relation between image segmentation and graph partitioning can be seen in Fig. 3. Methods that use graphs for image segmentation[13] have been widely investigated within the fields of image processing and image understanding. In these methods, segmentation problems by analogy are translated into graph based problems and that are solved as the graph partitioning problem. These graph based segmentation methods might be grouped as (1) graph cut based methods, (2) interactive methods, (3) minimum

spanning tree based methods and (4) pyramid based methods.

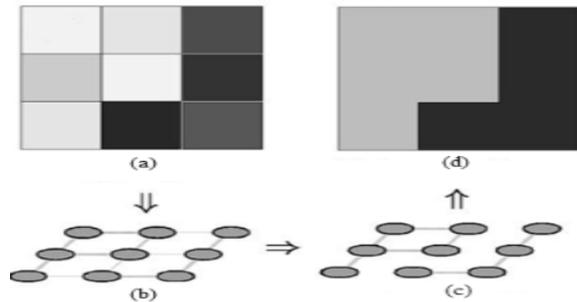


Fig. 3. Association between image segmentation and graph partition
 (a) Image (b) Graph (c) Graph partition (d) Segmented image.

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BIOGRAPHY



Miss. H.P. Narkhede is working as Assistant professor at J.T. Mahajan College Of Engineering, Faizpur. She received the B.E. Degree in Electronics and Telecommunication from Department Of Electronics and Telecommunication Engineering, North

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IV. CONCLUSION

Graph cuts are simply a minimum cut on a given graph. This cut segments images into two regions. Because the minimum cut is equivalent to the maximum flow, many graph cut algorithms actually compute the maximum flow instead of the minimum cut. There has been increasing interest in using graph based methods as a powerful tool for major graph based methods and highlighted their strengths as well as limitations. Some difficulties of these methods have brought down their use in practical applications. For that, the primary reason is the higher computational complexity such that the vertex or an edge in a graph requires polynomial time segmenting images. This review has discussed some of the major graph based methods and highlighted their strengths.