Image segmentation using graph-cuts

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Abstract—The study provides a detailed overview of image segmentation techniques using graph cuts. Image segmentation is a crucial aspect of computer vision and image processing, with many applications such as medical imaging and object recognition. The Graph Cut technique applies graph theory to image processing to achieve fast image segmentation. Graph cuts algorithms aim to minimize an energy function that represents the cost of dividing the image into segments. This study discusses the ideas, methods, advantages, and applications of graph cuts in image segmentation.

Index Terms—Image segmentation, graph cuts, graph theory

I. Introduction

Image segmentation is a crucial aspect of computer vision and image processing, as it enables machines to understand visual input by breaking down images into relevant sections. These sections often correspond to objects or areas of interest, and are essential for various applications such as medical image analysis, autonomous navigation, and object recognition. Graph cuts algorithms are advanced methods for image segmentation that efficiently and accurately divide images into coherent fragments. Through image segmentation, raw pixel data is transformed into higher-level representations, allowing robots to interpret visual surroundings similar to how humans do. Graph cuts utilize graph theory for segmentation. By representing an image as a graph, with nodes representing pixels and edges indicating connections between them this project focuses on using graph cuts to split an image into background and foreground segments. The skeleton consists of two parts. First, a network flow graph is built based on the input picture. Then a max-flow algorithm is run on the graph in order to find the min-cut, which gives the optimal segmentation.

II. Literature Review

A. Related work

In this review of literature, we explore five key studies on using graph cuts for image segmentation. The first study looked at how binary graph cuts can efficiently segment objects and incorporate visual cues. The second study introduced a new method for min-cut/max-flow, which proved to be highly efficient for 2D grid graphs. The third study discussed normalized cut for perceptual grouping, highlighting its ability to extract overall impressions and arrange them hierarchically. In the fourth study, researchers looked into how graph cuts can be used for interactive image segmentation, allowing users to outline areas for segmentation and achieve the best possible results. The fifth study presented a graph model for image segmentation using predicates, which offers a fast algorithm with low time complexity. This method is particularly good at preserving intricate details in different parts of an image. Together, these studies contribute significantly to the field of image segmentation by offering various approaches that achieve accurate, fast, and interactive segmentation through the use of graph cuts. [Table-1]

III. Proposed Methodology

A. Pre-processing

Kernel density estimation (KDE) is used to capture pixel intensity distributions. It is an example of a probability density function of the pixel intensity of a KDE image. For each labeled point (foreground and background), KDE is used to estimate the probability that a pixel belongs to that class (foreground or background). The KDE for each color channel (RGB) is calculated separately, resulting in three KDE models. This step helps define possible pixel intensities associated with foreground or background regions.

B. Algorithms and Implementation

We used Ford-fulkerson algorithm for image segmentation.

Step-1 : Foreground and Background Scribbling, Step-2 : Graph Construction and Optimization, Step-3 : Segmentation Result. The segmentation process starts with the construction of a Directed Graph (G) to represent the given image. Each pixel in the image corresponds to a node in the graph, and edges are added between nearest pixels. The weights of these edges are chosen by a Bilateral Pixel Similarity Function which computes the similarity between two pixels based on their color intensities. It gives higher weights to edges which connects similar pixels.After this step, the Graph Cuts algorithm is applied for image segmentation. In this method the graph is augmented with source and sink nodes, which represents the foreground and background classes, respectively. After that edges are added from the source node to the non-scribbled pixels, with capacities based on the estimated chance of being foreground. In the same way, edges are added from the background scribbled points to the sink node, with capacities based on the estimated probability of being background. Foreground and background scribbled points are connected to the source and sink nodes, respectively, with fixed

TABLE I LITERATURE REVIEW TABLE

Research Article	Methodology Type	Datasets	Performance Technology
[1] Graph Cuts and Efficient N-D Image Segmentation	Binary Graph Cuts, Combinatorial Optimization Framework	Various (Synthetic, Realworld)	Global optima, practical efficiency, numerical robustness and Connections with earlier segmentation methods
[2] An Experimental Comparison of Min-Cut/Max-Flow Algorithms for Energy Minimization in Vision	Min-Cut/Max-Flow Algorithms Comparison, New Algorithm Development	Typical Vision Graphs (2D and 3D)	Developed new algorithm outperforming others in efficiency, Several times faster than push-relabel and Dinic algorithms
[3] Normalized Cuts and Image Segmenta-tion	Normalized Cut, Global Graph Partitioning	Static Images, Motion Sequences	Global impression extraction for image segmentation, Optimized using generalized eigenvalue problem, Encouraging results on real and synthetic images
[4] Interactive graph cuts for optimal boundary region segmentation of objects in N-D images	Graph Cuts with Interactive Marking	Photo/Video Editing, Medical Imaging	Unrestricted topol segments can have mul pa tiple in Application photo/vi and editing medical imaging Fast implementation with r new flow algorithm
[5] Efficient GraphBased Image Segmentation. International Journal of Computer Vision	Predicate-based Graph Representation	Real and Synthetic Images	Efficient segmentation algorithm with greedy decisions , Satisfies global properties, Fast in practice, nearly linear time complexity

capacities. The method then computes the minimum cut in the graph. This minimum cut divides the graph into two parts: 1) pixels belonging to the foreground and 2) pixels belonging to the background. To identify the minimum cut a function which uses Breadth-First Search (BFS) algorithm is used. Then, the residual capacities are used to identify reachable nodes from the source after the flow is calculated, with the remaining nodes making the cut separating foreground and background regions.

IV. RESULTS

Image segmentation using Graph Cuts with KDE-based preprocessing provides an efficient and interactive method for foreground and background separation. By combining pixel intensity classification and two-dimensional pixel shape, the algorithm achieves an accurate classification based on the scripts used by the user This method keeps a balance between user input (scribbles) and automatic segmentation, and makes it suitable for a wide range of applications in computer vision and image processing. We have used one horse image in the implementation which was segmented in three areas. Horse, Sky and land. We have also tried the segmentation of various other images using the above algorithm and observed significant performance.This approach can be helpful in the fields like medical image segmentation, object based or color based segmentation etc.

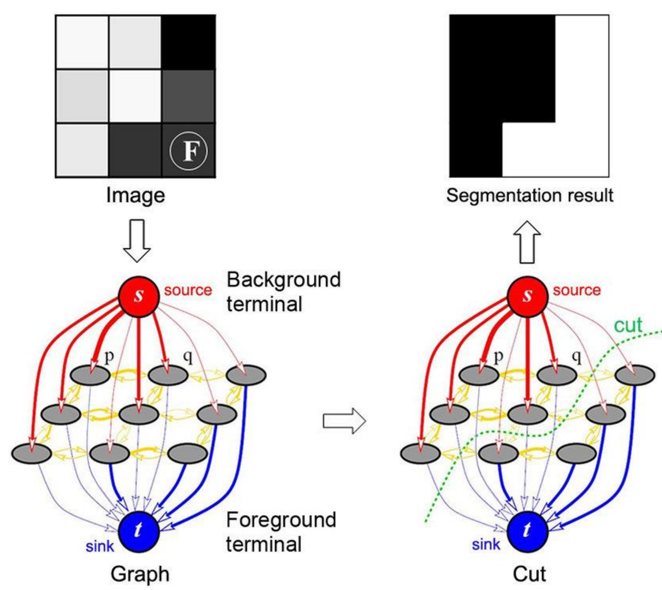

Fig. 1. Reduced size image.

Fig. 2. Reduced size image.

V. Conclusion

In conclusion, the implementation of image segmentation using graph cuts has showed significant promise in accurately partitioning images into meaningful regions. Through this study, we have explored the application of graph cuts in solving the NP-hard problem of image segmentation, offering efficient and effective solutions.Our results highlight the versatility of graph cuts, showing its ability to handle various types of images with complex structures and diverse textures. By formulating image segmentation as a graph partitioning problem, we have achieved impressive segmentation results, as demonstrated by the visual quality and quantitative metrics such as precision, recall, and F1-score. Moreover, the implementation process has shed light on important factors such as parameter tuning, graph construction, and energy minimization techniques. These insights are valuable for researchers and practitioners hoping to leverage graph-based approaches for image segmentation tasks. Looking ahead, further study can explore improvements to the current implementation, such as integrating higher-order potentials, incorporating deep learning features, or extending the method to 3D image volumes. Additionally, exploring real-time applications and scalability to larger datasets would be promising paths for future work. In summary, our implementation of image segmentation using graph cuts has given a solid basis for understanding and utilizing this powerful technique. It opens doors to a range of applications in computer vision, medical imaging, and more, giving precise and efficient solutions to the problem of image analysis and interpretation.

References

[1] Boykov, Y., Funka-Lea, G. (2006). Graph cuts and efficient N-D image segmentation. International Journal of Computer Vision, 70(2), 109–131. https://doi.org/10.1007/s11263-006-7934-5

[2] Boykov, Y., Kolmogorov, V. (2004). An experimental comparison of min-cut/max- flow algorithms for energy minimization in vision. IEEE Transactions on Pattern Analysis and Machine Intelligence, 26(9), 1124–1137. https://doi.org/10.1109/tpami.2004.60

[3] Shi, J., Malik, J. (2000). Normalized cuts and image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 22(8), 888–905. https://doi.org/10.1109/34.868688

[4] Boykov, Y., Jolly, M. (2002). Interactive graph cuts for optimal boundary region segmentation of objects in N-D images. IEEE. https://doi.org/10.1109/iccv.2001.937505

[5] Eriksson, A., Barr, O., Astr˚om, K. (2006). Efficient Graph-Based¨ Image Segmentation. International Journal of Computer Vision, 45–48.

In [6]:
```
import numpy as np
import cv2
import networkx as nx
import matplotlib.pyplot as plt
from scipy.stats import multivariate_normal
from sklearn.neighbors import KernelDensity
from networkx.algorithms.flow import maximum_flow
from tqdm import tqdm
from networkx.algorithms.flow import edmonds_karp
from scipy.stats import gaussian_kde
```

In [7]:
```
def bpq(ip, iq, sigma):

    return np.exp(-((np.linalg.norm(ip - iq)) ** 2) / (2 * sigma ** 2))
```

In [8]:
```
def find_min_cut(G,  sink,source):

    def residual_capacity(u, v):
        return G[u][v].get('capacity', 0) - G[u][v].get('flow', 0)

    def bfs(G, source, sink, parent):
        visited = set()
        queue = []
        queue.append(source)
        visited.add(source)

        while queue:
            u = queue.pop(0)

            for v in G.successors(u):
                if v not in visited and residual_capacity(u, v) > 0:
                    queue.append(v)
                    visited.add(v)
                    parent[v] = u

        return visited

    parent = {}
    max_flow = 0

    while bfs(G, source, sink, parent):
        path_flow = float('inf')
        s = sink
        while s != source:
            path_flow = min(path_flow, residual_capacity(parent[s], s))
            s = parent[s]

        max_flow += path_flow
```

APPENDIX: PYTHON CODE

```
        v = sink
        while v != source:
            u = parent[v]
            flow_in = G[u][v].get('flow', 0)
            flow_out = G[v][u].get('flow', 0)
            G[u][v]['flow'] = flow_in + path_flow  # Update flow on forward edge
            G[v][u]['flow'] = flow_out - path_flow  # Update flow on reverse edge (if it exists)
            v = u

    # Identify the minimum cut based on residual capacities
    reachable_nodes = bfs(G, source, sink, parent)  # Nodes reachable from source
    cut_nodes = list(set(G.nodes) - reachable_nodes)  # Remaining nodes

    return reachable_nodes, cut_nodes
```

In [9]:

```
def segment_image(img, fg_points, bg_points, sigma=0.7, lamda=1):
    # Create a directed graph
    g = nx.DiGraph()

    h, w, _ = img.shape
    nodeids = [(i, j) for i in range(h) for j in range(w)]
    g.add_nodes_from(nodeids)

    # Add edges between neighboring pixels with weights based on similarity
    for i in range(h):
        for j in range(w):
            if j > 0:

                g.add_edge((i, j), (i, j - 1), capacity=bpq(img[i, j], img[i, j - 1], sigma))
            if i > 0:

                g.add_edge((i, j), (i - 1, j), capacity=bpq(img[i, j], img[i - 1, j], sigma))

    # Add source and sink nodes
    source_node = (-1, -1)  # Source node
    sink_node = (-2, -2)    # Sink node
    g.add_node(source_node)
    g.add_node(sink_node)

    import numpy as np

    def intensity_distribution(image,pixel_coords):
        # Extract intensity values from pixel coordinates
        def get_intensity(coord):
            return image[coord[0], coord[1]]
        intensity_values = [get_intensity(coord) for coord in pixel_coords]

        # Create KDE of intensity values
        intensity_values_split = list(zip(*intensity_values))


        kder = gaussian_kde(intensity_values_split[0])
        kdeg = gaussian_kde(intensity_values_split[1])
        kdeb = gaussian_kde(intensity_values_split[2])
```

```python
    # Function to get intensity value of a pixel

    plus=0.000001
    # Function to calculate probability for another pixel
    def probability_for_pixel(other_coord):
        intensity = get_intensity(other_coord)
        return (kder.evaluate(intensity[0])[0]+plus)*(kdeb.evaluate(intensity[1])[0]+plus)*(kdeb.evaluate(intensity[2])[0]+plus)

    return probability_for_pixel


probability_function_fg = intensity_distribution(img,fg_points)
probability_function_bg = intensity_distribution(img,bg_points)

# Add edges from source node to non-scribbled pixels
for node in nodeids:
    if node not in fg_points and  node not in bg_points:
        g.add_edge(source_node, node, capacity=probability_function_fg(node))
        g.add_edge(node, sink_node, capacity=probability_function_bg(node))

# Add edges from foreground points to source and sink nodes
for fg_p in fg_points:
    g.add_edge(source_node, fg_p, capacity=float(1))
    g.add_edge(fg_p, sink_node, capacity=float(0))


# Add edges from background points to source and sink nodes
for bg_p in bg_points:
    g.add_edge(source_node, bg_p, capacity=float(0))
    g.add_edge(bg_p, sink_node, capacity=float(1))


cut_value, partition = nx.minimum_cut(g, (-1, -1), (-2, -2))


return list(partition[0]), list(partition[1])
```

In [10]:

```python
def draw_segment(event, x, y, flags, param):
    global drawing, prev_point, fg_points, bg_points, img_display
    if event == cv2.EVENT_LBUTTONDOWN:
        drawing = True
        prev_point = (x, y)
    elif event == cv2.EVENT_MOUSEMOVE:
        if drawing:
            if flags & cv2.EVENT_FLAG_CTRLKEY:
                cv2.line(img_display, prev_point, (x, y), (0, 255, 0), thickness=5)  # Draw green line for background
                bg_points.append((y, x))  # Add point to background points
            else:
                cv2.line(img_display, prev_point, (x, y), (0, 0, 255), thickness=5)  # Draw red line for foreground
                fg_points.append((y, x))  # Add point to foreground points
            prev_point = (x, y)
    elif event == cv2.EVENT_LBUTTONUP:
        drawing = False
```

In [*]:

```
# Load the image
img = cv2.imread("p1.jpg")


img_display = img.copy()

cv2.namedWindow("Draw Foreground and Background Segments")
cv2.setMouseCallback("Draw Foreground and Background Segments", draw_segment)

drawing = False
prev_point = None
fg_points = []
bg_points = []


cv2.namedWindow("Draw Foreground and Background Segments")
cv2.setMouseCallback("Draw Foreground and Background Segments", draw_segment)

# Main loop
while True:
    cv2.imshow("Draw Foreground and Background Segments", img_display)
    key = cv2.waitKey(1) & 0xFF
    if key == ord("s"):
        # Segment the image
        print('Processing...')
        fg_segment, bg_segment = segment_image(img, fg_points, bg_points)
        # Create blank images with the same dimensions as the original image
        foreground_img = np.zeros_like(img)
        background_img = np.zeros_like(img)

        # Get the dimensions of the original image
        height, width, _ = img.shape


        # Construct the foreground segment image
        for coord in fg_segment:
            x, y = coord
            foreground_img[x, y] = img[x, y]

        # Construct the background segment image
        for coord in bg_segment:
            x, y = coord
            background_img[x, y] = img[x, y]

        fig, axes = plt.subplots(1, 4, figsize=(24, 6))

        # Original image
        axes[0].imshow(cv2.cvtColor(img, cv2.COLOR_BGR2RGB))
        axes[0].set_title("Original Image")
        axes[0].axis('off')

        # Foreground segment
        axes[2].imshow(cv2.cvtColor(foreground_img, cv2.COLOR_BGR2RGB))
        axes[2].set_title("Foreground Segment")
        axes[2].axis('off')

        # Background segment
        axes[3].imshow(cv2.cvtColor(background_img, cv2.COLOR_BGR2RGB))
        axes[3].set_title("Background Segment")
        axes[3].axis('off')

        # Drawn image
        axes[1].imshow(cv2.cvtColor(img_display, cv2.COLOR_BGR2RGB))
        axes[1].set_title("Drawn Image")
        axes[1].axis('off')

        plt.tight_layout()
        plt.show()

    elif key == ord("q"):
        break

cv2.destroyAllWindows()
```