Graph based Image Segmentation

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Abstract

Here, we address the problem of segmenting image into different regions. We first convert the image into a graph based representation by first constructing the superpixels by using Simple Linear Iterative Clustering (SLIC) based on the spatial proximity and the color proximity and then giving edge weights by setting a specific threshold. To segment this image, we then cluster the graph into multiple clusters. Different clusters form different segments of the image.

1 Introduction

Image segmentation is an important part of Image Analysis. It is of great practical importance and has been the interest of research for a long time. Image segmentation has been very useful in tasks such as Object detection and recognition, content based image retrieval, video surveillance, traffic control systems, medical imaging and many other tasks.

Classical Image Segmentation techniques are based on color and edge detection. This edge or boundary is generally found out by taking the gradient in the image. In this segmentation technique, we construct the superpixels of the image and then build a graph from these superpixels and give them edge weights by setting a specific threshold and then cluster the graph to get multiple segments.

2 Background

2.1 Graph Notation

Let G = (V, E) represent an undirected graph where $v_i \in V$ are the vertices/nodes of the graph (each node corresponds to a superpixel) and $(v_i, v_j) \in E$ are the edges of the graph (the edges connecting two superpixels). The adjacency wieghted matric of the graph $W = w_{ij}$ where $i, j = 1, 2, \ldots, n$. If $w_{ij} = 0$, then the vertices v_i and v_j are not connected. As this is an undirected graph, we have $w_{ij} = w_{ji}$. The degree of a vertex v_i is

$$d_i = \sum_{j=1}^{n} w_{ij}$$

The degree matrix D is a diagonal matrix with d_i at its i_{th} diagonal or at D(i,i).

2.2 Graph Laplacian

The unnormalized graph laplacian is defined as

$$L = D - W$$

. The normalized graph laplacians are defined as

$$L_{sym} = D^{-1/2} L D^{-1/2} = 1 - D^{-1/2} W D^{-1/2}$$
$$L_{rw} = D^{-1} L = 1 - D^{-1} W$$

where L_{sym} is the symmetric graph laplacian and L_{rw} is the random walk graph laplacian.

3 Implementation

3.1 Constructing Superpixels

Superpixels are basically a group of pixels which can be used to replace the rigid structure of the pixels and they are convenient to compute image features. Superpixels fit well to image boundaries based on the edges and the colors and they improve the speed and quality of image segmentation.We construct the superpixels of the image by Simple Linear Iterative Clustering (SLIC) which is a state of the art boundary adherence. It is based mainly on spatial proximity and colour proximity.

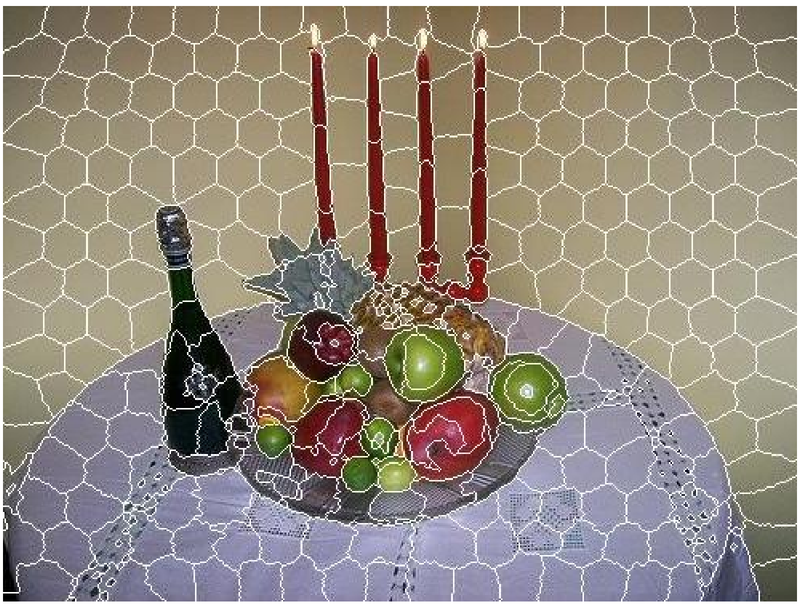


Figure 1: Image with its superpixel boundaries in white lines

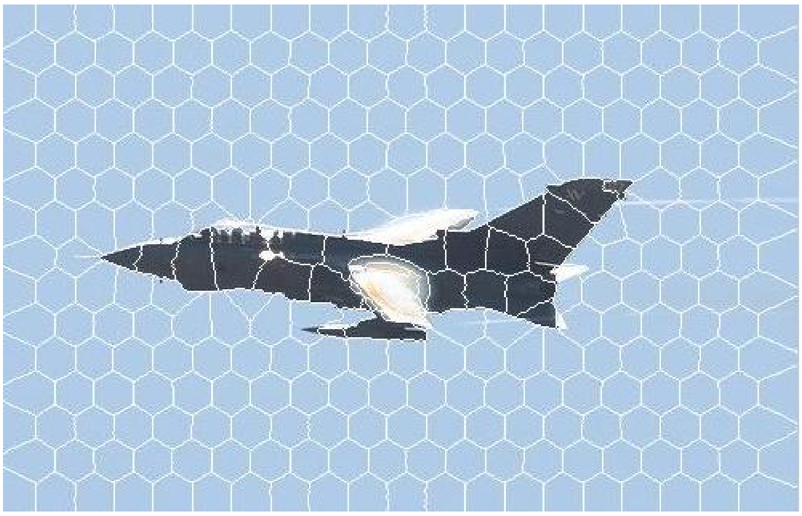


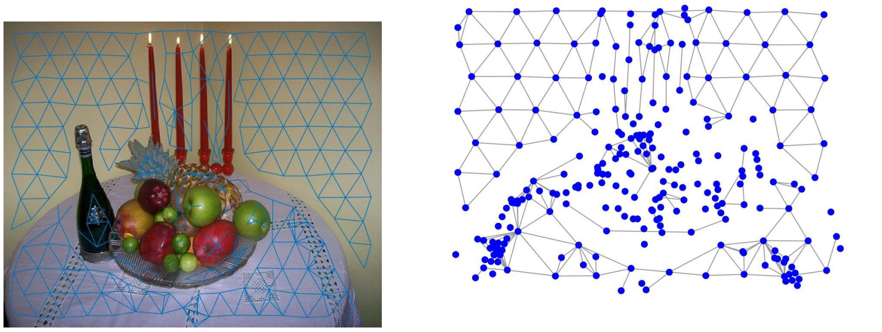
Figure 2: Another image with its superpixel boundaries in white lines

3.2 Extracting Feature Descriptor

In Computer Vision, a feature descriptor is a descriptor of the visual features of the contents present in images or videos. They describe the characteristics such as the shape, the color, the texture or the motion, among others. We extract SIFT descriptor and L*a*b color values for each pixel of the superpixel. We then encode this SIFT descriptor and L*a*b color values by using Fisher vectors. We take local feature descriptors of the pixels and encode them into higher dimensional vector to get a feature descriptor for the superpixel. This is done this by the implementation used by VlFeat.

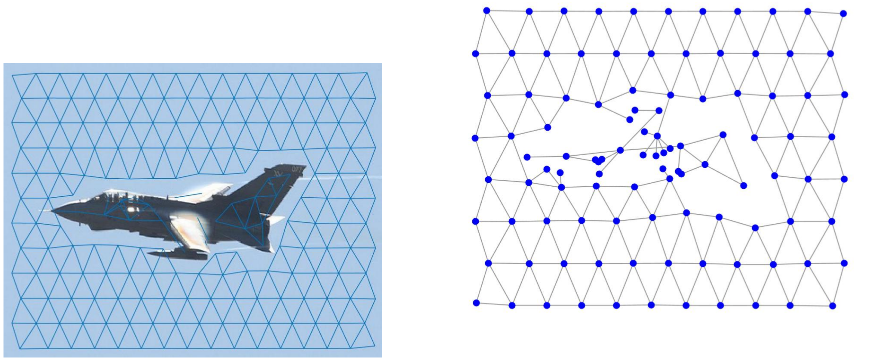
3.3 Constructing the graph

We use the feature descriptors for finding the edge weights by taking each superpixel as a node and computing the Gaussian for the edge weights (also known as similarity). We keep a threshold for the edge weights and any edge with less that that weight will be considered non-existant.



(a) Graph on an image (b) Graph of the image on a white background

Figure 3: Graph constructed from the superpixels of an image



(a) Graph on an image (b) Graph of the image on a white background

Figure 4: Graph constructed from the superpixels of an image

From the above constructed graph, we can see that different segments of the image are sparsely connected in the graph. So, this is how clustering the graph into different segments will help in segmenting the image.

3.4 Clustering the graph

Here, we try to solve the problem of binomial segmentation. We can also use this same method for semantic segmentation. We use Normalized Spectral Clustering using either Symmetric Graph Laplacian or Random Walk Graph Laplacian to separate the image into two clusters. The computation of this Laplacian, its eigenvectors and eigenvalues are done by using "The Graph Signal Processing Toolbox (GSPBox)" present in MATLAB.

To cluster it into k clusters, we take the first k eigenvectors of the Laplacian and make a matrix with these eigenvectors as columns and then use the classical clustering k-means algorithm to cluster in into k clusters. This method is more efficient and faster than the k-means algorithm and the computation is easier as it can be solved by standard linear algebra methods. For binomial segmentation, the graph is separated into two clusters (k=2) using Spectral Clustering. This computation is done by using "The Compressive Spectral Clustering Toolbox" present in MATLAB.

In the above results I have represented the nodes of the superpixels which belong to one of the cluster in blue dots. (i.e. the part which belongs to one segment of the image or the foreground of the image as this is binomial segemntation and there are only two segments to it - the foreground and the background.).

4 Results

As shown above, this method works very well for binary segmentation. But, in the case of semantic segmentation, while clustering with k>2, we do not have a fixed k and we will have to figure it out from the image which might become a little complicated. One way of approaching that problem is to recursively perform clustering with k=2 until we do not need to segment further. Below are the results from semantic segmentation for images containing multiple objects where the accuracy is not so good.

5 Summary and Conclusion

We address the problem of segmenting an image into different regions. We segment the image into two regions by constructing a graph and utilizing it to cluster it into two regions.

Here, we try to segment the image by first constructing the superpixels of the image. Then we take each one node from each superpixel and construct a graph from it. We give edge weights by using feature descriptors such as SIFT and L*a*b color values by setting a specific threshold. We then cluster this graph into 2 regions to cluster the image.

References

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