GRAPH THEORY BASED IMAGE SEGMENTATION ON IMAGE PROCESSING TECHNIQUES

K. SUREKA [1], C. CHITHIRAISELVI[2]
Mphil Research Scholar, Department of Maths , PRIST University., THANJAVUR
Assistant Professor, Department of Maths , PRIST University., THANJAVUR

subhijose2006@gmail.com

Abstract— Image segmentation is a fundamental process in many image, video, and computer vision applications. It is very essential and critical to image processing and pattern recognition, and determines the quality of final result of analysis and recognition. This project presents a semi-supervised strategy to deal with the issue of image segmentation. Each image is first segmented coarsely, and represented as a graph model. Then, a semi-supervised algorithm is utilized to estimate the relevance between labeled nodes and unlabeled nodes to construct a relevance matrix. Finally, a normalized cut criterion is utilized to segment images into meaningful units. The experimental results conducted on Berkeley image databases and MSRC image databases demonstrate the effectiveness of the proposed strategy.

Keywords – Image Segmentation, bereley image data base, Graph theory

I INTRODUCTION

Pictures are the most common and convenient means of conveying or transmitting information. A picture is worth a thousand words. Pictures concisely convey information about positions, sizes and inter-relationships between objects. They portray spatial information that we can recognize as objects. Human beings are good at deriving information from such images, because of our innate visual and mental abilities. About 75% of the information received by human is in pictorial form.

Digital image processing

The analysis of a picture using techniques that can identify shades, colors and relationships that cannot be perceived by the human eye. Image processing is used to solve identification problems, such as in forensic medicine or in creating weather maps from satellite pictures. It deals with images in bitmapped graphics format that have been scanned in or captured with digital cameras.

An image may be defined as a two dimensional function f(x, y),Where x and y are spatial Co-ordinates, and the amplitude of 'f' at any pair of Co-ordinates (x,y) is called the intensity or gray level of the image that point. When x, y and the amplitude values of 'f' are all finite, discrete quantities. We call the image a digital image. A digital image is composed of a finite number of elements, each of which has a particular location and value. These elements are referred to as picture elements, image elements, pels and pixels.

Examples of field that use Digital Image Processing:
1. Gamma-Ray imaging
2. X-Ray Imaging
3. Imaging in the Ultraviolet Band
4. Imaging in the Visible and Infrared Bands
5. Imaging in the Microwave Band
6. Imaging in the Radio Band

Image enhancement

It is the process of manipulating an image so that the result is more suitable than the original for a specific application. The word specific is important here, because it establishes at the outset that enhancement techniques are problem oriented. Thus for example, a method that is quite useful for enhancing X-ray images may not be the best approach for enhancing the satellite images taken in the infrared band of the electromagnetic spectrum

Image Restoration

The principal goal of restoration techniques is to improve an image in some predefined sense. Image restoration is objective, in the sense that restoration techniques tend to be based on mathematical or probabilistic models of degradation. Although there are areas of overlap, image enhancement is largely a subjective process, while image restoration is for the most part an objective process. Restoration attempts to recover an image that has been degraded by using a prior knowledge of the degradation phenomenon. Thus restoration techniques are oriented toward modeling the degradation and applying the inverse process in order to recover the original image.

This approach usually involves formulating a criterion of goodness that will yield an optimal estimate of the desired result. By contrast, enhancement techniques basically are heuristic procedures designed to manipulate an image in order to take advantage of the psychophysical aspects of the human visual system. For example, contrast stretching is considered an enhancement technique because it is based primarily on the pleasing aspects it might present to the viewer; wheras removal of image blur by applying a deblurring function is considered a restoration technique.

Image compression

It refers to the process of reducing the amount of data required to represent a given quantity of information. In this definition, data and information are not the same thing. Data are the means by which information is conveyed. Because various amounts of data can be used to represent the same amount of information, representations that contain irrelevant or repeated information are said to contain redundant data. It is one of the most useful and commercially succesful technologies in the field of digital image processing. The number of images that are compressed and decompressed daily is staggering, and the compressions and decompressions themselves are virtually invisible to the user.The objective is to reduce redundancy of the image data in order to be able to store or transmit data in an efficient form.

Image compression can be lossy or lossless. Lossless compression is sometimes preferred for artificial images such as technical drawings, icons or comics. This is because lossy compression methods, especially when used at low bit rates, introduce compression artifacts. Lossless compression methods may also be preferred for high value content, such as medical imagery or image scans made for archival purposes. Lossy methods are especially suitable for natural images such as photos in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate.

Image Segmentation

It refers to the process of partitioning a digital image into multiple segments (sets of pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.[1] Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain visual characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

Some of the practical applications of image segmentation are:

- Medical Imaging
  - Locate tumors and other pathologies
  - Measure tissue volumes
  - Computer-guided surgery
  - Diagnosis
  - Treatment planning
  - Study of anatomical structure
- Locate objects in satellite images (roads, forests, etc.)
- Face recognition
- Fingerprint recognition
- Traffic control systems
- Brake light detection
- Machine vision

Image reconstruction

The reconstructing an image from a series of projections, with a focus on X-ray computed tomography. This is the earliest and still the most widely used type of CT and is currently one of the principal applications of digital image processing in medicine. It is simple in principle and can be explained qualitatively in a straightforward, intuitive manner.

II RELATED WORK

Iterated Graph Cuts for Image Segmentation

In this technique, an iterated graph cuts algorithm is very briefly explained, which begins from the sub-graph of graph which represents an image. This includes the user labeled foreground or background regions. This technique works iteratively to label the neighboring un-segmented regions or image segments. During the process of each iteration the local neighboring regions or segments to the labeled regions only are tangled in the optimization so that considerable interference from the unknown regions which are very far can be ominously reduced. In order to get better efficiency and robustness of image segmentation, the mean shift method to divide the image into homogenous regions is used, and then the iterated graph cuts algorithm is implemented by compelling each region, rather than every pixel, as the graph node for image segmentation. Widespread experiments on benchmark datasets revealed that this technique contributes much improved image segmentation results than the typical graph cuts and the GrabCut approaches in both quality and quantity aspect of calculations. Another important advantage is that it is impervious to the parameter in optimization [14].

Segmentation using minimal spanning trees

A minimum spanning tree (MST) is subgraph of a tree with minimum-weight, containing no cycles such that all nodes are connected. Felzenszwalb presented a segmentation method [16] which is based on Kruskal's MST algorithm method in the year 2004. According to this algorithm, edges are quantified in increasing order of their weight. The endpoint pixels of edges are combined into a region. Pixel similarity is adjudicated by a heuristic, which compares the weight of an each segment threshold. The algorithm outputs a forest which is a multiple disjunction Minimal Spanning Trees (MSTs), where each tree represents a segment.

Wassenberg et al. developed an algorithm [17] in 2009, which computes multiple autonomous Minimum Spanning Forests and then stitches them collectively. This allows parallel processing without dividing objects on tile borders. As an alternative, a constant weight threshold i.e., an initial connected component labeling is used to estimate a lower bound on the threshold, which further can cause the reduction of both over segmentation and under segmentation. Calculations show that the implementation outclasses Felzenszwalb's sequential algorithm method by the directive of magnitude. Segmentation results are satisfactory and are not sensitive to noise.

Segmentation using Euler Graphs

This technique explains an algorithm for image segmentation problem using the concepts of Euler graphs in graph theory. Here the image is treated as an undirected weighted nonplanar finite graph (G), and then image segmentation is treated as graph partitioning problem. This method locates region boundaries or clusters and runs in polynomial time. Subjective comparison and objective estimation shows the efficiency of the method in different image domains. The algorithm begins by randomly choosing an edge and tries to form closed regions. During the process, open paths are formed. The color look up table is used for the edges to trace their transition. A white color indicates unvisited edge, a gray color indicates visited edge and may go for the refinement and black color indicates visited and marked permanently for no refinement as it is already a part of a region boundary. This method runs in polynomial time [9].

III PROPOSED WORK
GRAPH THEORY BASED IMAGE EVALUATIONS AND SEGMENTATIONS

First we need to represent the original image as an undirected weighted graph $G = (V,E)$. The nodes of the graph will be the pixels of the image and between each pair of nodes i , j we need to decide on a weight to the edge. This is an important question because we will decide how to disjoint a group of nodes according to the weights of the edges between them.

This weight of each edge is the core of the ahead computation. We want to assign big weight on edges between nodes that shouldn't be in the same segmented group. So we need to choose a weight that points on the similarity between the two nodes.

Subjectively we are grouping parts of image to different objects according to prior knowledge about those objects. This kind of segmentation acquires huge databases on each kind of possible object and is likely unpractical.

Instead I used the objective approach which relies on the image low level properties. But what low level properties we can use when our image is an array of numbers.These values of each pixel implies on their intensity, so a good criterion for an edge weight will be the intensity differences, because we want to disjoint nodes with meaningful intensity difference. Than we give each node a value and define that the weight of an edge between two nodes is the difference between their values. But is that all we can now just group together the nodes with similar intensity and get a good segmentation well not exactly. If two nodes got the same intensity they are not necessarily belong to the same segment object, because they could belong to different objects that got parts with the same intensity. There for we need that the weight of edge between tow nodes should be affected also by the length between the nodes. But still we got another image low level property that we are not taking advantage of color. While intensity distinguishes different brightness, its ability to distinguish between different colors is limited. In order to measure differences between colors I used the indexed image representation which represent a color image I as a pair of <X,colormap>. Where each entry in the colormap is a different color. And the colors arranged in the map in the colormap in ascending order:

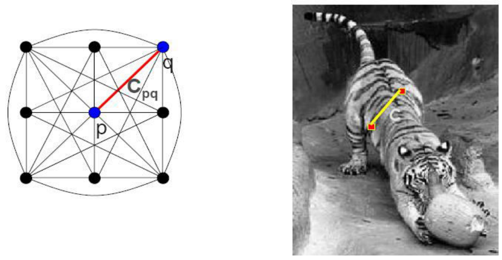

Fig 1: Graph Representation

1. Given an image, set up a weighted graph G=(V, E) and set the weight on the edge connection two nodes to be a measure of the similarity between the two nodes.
2. Compute W,D
3. Solve for the eigenvectors of
4. Use the eigenvector of the second smaller eigenvalue to bipartition the graph.
5. Decide if the current partition should be subdivided and recursively repartition the segmented parts if necessary.

Where in step 5 Decide if the current partition should be subdivided bychecking the stability of the cut by making sure the founded Ncut is below the pre-specified threshold value.

All the steps were implemented in matlab (6.5 version) and a matlab gui performing all the above is the final result.

that there is the analysis of the packet delivery ratio compare with existing and proposed methodology.

IV RESULTS AND DISCUSSION

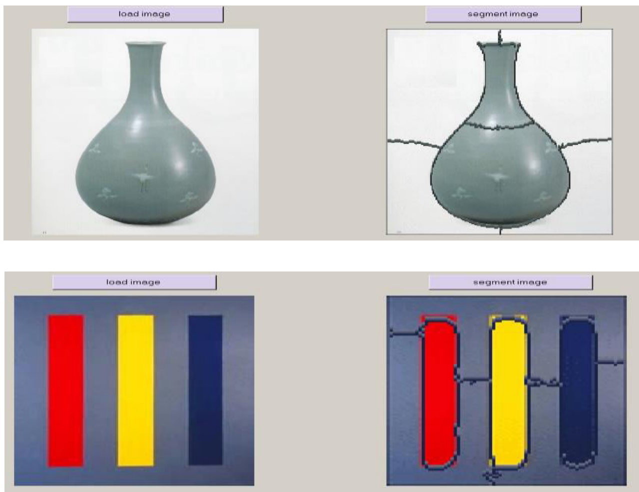

Fig. 2 Sample Object

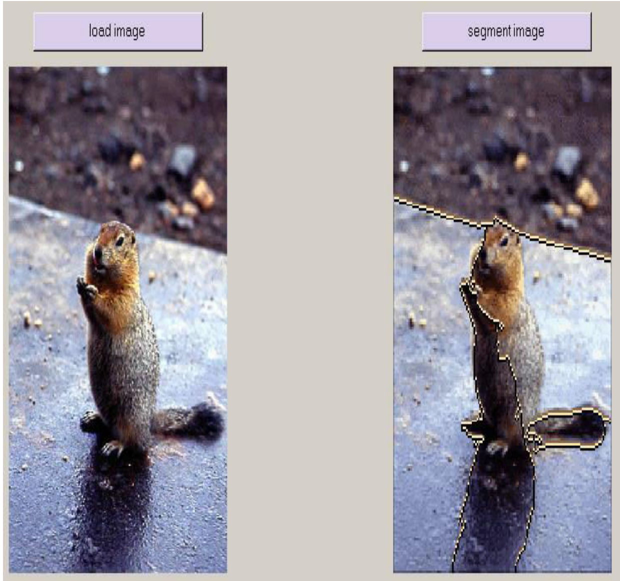

Fig: 3 On object that is similar to the background

IV CONCLUSION

As you can see the program is far from being perfect. Nevertheless It evolves good results with concerning to simple objects that their background is whether uniform or not. We can regard this success to the good weight assigning of the associate graph and to the Ncut algorithm which chooses to divide only non-similar regions that are significant enough. The application is also very convenient, simple and friendly to the user. That due to the matlab gui which wraps the program and enables the simplicity. With concerning to efficiency the program run-time on a 2.5 GHz is up to 1.3 minutes depending on the image resolution. Though the commutation time of solving $(D-W)y = \lambda Dy$ takes O(n^3) I performed preprocessing on the original image that resize the original resolution down to a certain threshold. This comes off course on the account of the accuracy of the image processing. This is a very meaningful factor that could be improved in the future by simplify the computation of $(D-W)y = \lambda Dy$ (with Lanczos method for example).Using the indexed representation to distinguish between colors is efficient only on nodes of very different colors this can be regarded to the matlab default color map which its size is 132. it might be that adding more kinds of colors to the map, meaning using bigger map could improve the results. Another possible improvement is finding a more efficient computation to achieve texture similarity that could improve the results by improving the similarity measures (the weight function).All in all the program produce satisfying results consider the limitation of time and certainly could be a good starting point for anyone who is interesting in segmentation and its implementation.

REFERENCES

[1] H. Bunke, "Recent developments in graph matching", in Proceedings 15th Int. Conf. on Pattern Recognition, ICPR'2000, Barcelona, Spain, Vol. 2, pp. 117-124, 2000.

[2] H. Bunke and A. Sanfeliu (eds.), Syntactic and Structural Pattern Recognition: Theory and Applications, World Scientific, 1990.

[3] R.C. Wilson and E.R. Hancock, "Structural matching by discrete relaxation", IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 19, pp. 634-648, 1997.

[4] J. Kittler, W.J. Christmas and M. Petrou, "Probalistic relaxation for matching problems in machine vision", Proc. 4th International Conference on Computer Vision, pp. 666-674, 1993.

[5] J. Vergés and A. Sanfeliu, "Colour image segmentation solving hard-constraints on graph partitioning greedy algorithms", Proc. 15th Int. Conf. on Pattern Recognition, ICPR'2000, Barcelona, Spain, Vol.3, pp. 629-632, 2000.

[6] J. Andrade and A. Sanfeliu, "Integration of perceptual grouping and depth", Proc. 15th Int. Conf. on Pattern Recognition, ICPR'2000, Barcelona, Spain, Vol.1, pp. 295-298, 2000.

[7] F. Serratosa and A. Sanfeliu, "Function-Described Graphs applied to 3D object recognition", in Proceedings ICIAP'97, 9th Int. Conf. Image Analysis and Processing, Firenze, Italy, Vol. I, pp. 701-708, 1997.

[8] R. Alquézar, A. Sanfeliu and F. Serratosa, "Synthesis of Function-Described Graphs", in Advances in Pattern Recognition, Proc. Joint IAPR Int. Workshops SSPR'98 and SPR'98, Sydney, Australia, Springer LNCS-1451, pp. 112-121, 1998.

[9] F. Serratosa, Function-Described Graphs for Structural Pattern Recognition, Ph.D. thesis dissertation, Universitat Politècnica de Catalunya, July 2000.

[10] A.K.C. Wong, J. Constant and M. You, "Random Graphs", Syntactic and Structural Pattern Recognition: Theory and Applications, H.Bunke and A.Sanfeliu (eds.), World Scientific, pp. 197-234, 1990.

[11] A.K.C. Wong and M. You, "Entropy and distance of random graphs with application to structural pattern recognition", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 7, pp. 599-609, 1985.

[12] A. Sanfeliu, F. Serratosa and R. Alquézar, "Clustering of attributed graphs and unsupervised synthesis of function-described graphs", in Proceedings 15th Int. Conf. on Pattern Recognition, ICPR'2000, Barcelona, Spain, Vol. 2, pp. 1026-1029, 2000.

[13] Z. Wu and R. Leahy, "An Optimal Graph Theoretic Approach to Data Clustering: Theory and Its Application to Image Segmentation", IEEE Trans. on Pattern Analysis and Machine Intelligence, Vol. 15, No. 11, pp. 1101-1113, 1993.