Dynamic N-Cut Image Segmentation

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***Abstract*: We propose a novel approach for solving the perceptual grouping problem in vision.We treat image segmentation as a graph partitioning problem and propose a novel global criterion, The Dynamic normalized cut, for segmenting the graph. We show that an efficient computational technique for calculating the number of segments dynamically. We have applied this approach to segmenting static images and found the results to be very encouraging.**

***Keywords*: segmentation, normalized cut, Hue Saturation value, Eigen values.**

I.INTRODUCTION

Image process could be a speedily growing space of technology. Its growth has been oil-fired by technological advances in digital imaging, laptop processors and mass storage devices. Fields which traditionally used Analogue imaging are now switching to digital systems, for their flexibility and affordability. Important examples are medicine, film and video production, photography, remote sensing, and security monitoring. Segmentation refers to the process of partitioning a digital image into multiple segments (sets of pixels, also known as super 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.

1.1 IMAGES AS GRAPHS

An image can be represented by graph with node at each pixel location. Edges represent relationships within pixel contents. Edges can be further weighted as similarity criterion as defined by affinity measure.

Affinity measure includes two measures: distance measure and intensity measure.

Distance measure: One way to define similarity between pixels is to find spatial distance between them. For this, the measurement that quickly falls with distance is desired, so we can define affinity as an exponential function of distance

aff(x,y)=exp{0-((x-y)^t(x-y)/2

Where controls how far away pixels effects current location. Intensity measure: Similar argument can be made regard to intensity. Pixels in near- by intensity place may be considered similar. Again exponential measure is needed to define how far away pixels interact.

II .GRAPH CUTS FOR IMAGE SEGMENTATION

Sorting pixel neighborhood based on affinity measure can produce good segmentation results. By formulating the problem as an optimization of affinity measure and solving using Lagrange multiplier [6], the following linear system needed to be solved:

$$Aw= w$$

Where w is the solution given by eigenvector of affinity matrix A

III .GROUPING ALGORITHM

The eigenvector corresponding to second smallest eigen value is the real valued solution that optimally partitions the entire graph, third eigen value partitions the first into two etc. Thus entire graph can be partitioned into subgraphs using the eigen vector with the next eigen value. Since approximation error accumulates with every eigen vector taken, so solution based on higher eigen vector becomes unreliable. Eigenvalue computation is very expensive. So Lanczos method for computation of Eigen vector of very sparse matrix is used where only couple of Eigen vectors is needed. Computation cost of Lanczos algorithm is typically less than O(n^ (3/2)) , where n is the number of nodes in the graph

Graph is partitioned using the second smallest eigen vector. Eigen vector takes on continuous values, so we need to define a splitting point for every eigen vector. Number of evenly spaced spiltting points in the range of eigenvector is checked and point that gives minimum Ncut value is chosen as a splitting point. The other approach is to take 0 or median value as a splitting point, but it is not reliable because of approximation error. The algorithm is recursively applied to every subgraph until Ncut value exceeds certain limit.

Another important property of this definition of associationand disassociation of a partition is that they are naturally related:

Unfortunately, minimizing normalized cut exactly is NP complete, even for the special case of graphs on grids. The proof, due to Papadimitriou, However, we will show that, when we embed the normalized cut problem in the real value domain, an approximate discrete solution can be found

$$\begin{aligned} Ncut(A,B) &= \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)} \\ &= \frac{assoc(A,V) - assoc(A,A)}{assoc(A,V)} \\ &\quad + \frac{assoc(B,V) - assoc(B,B)}{assoc(B,V)} \\ &= 2 - \left(\frac{assoc(A,A)}{assoc(A,V)} + \frac{assoc(B,B)}{assoc(B,V)}\right) \\ &= 2 - Nassoc(A,B). \end{aligned}$$

efficiently.

Hence, the two partition criteria that we seek in our grouping algorithm, minimizing the disassociation between the groups and maximizing the association within the groups, are in fact identical and can be satisfied simultaneously.

In our algorithm, we will use this normalized cut as the partition criterian

IV. EXISTING SYSTEM

There are many existing systems approaches available according to literature. Color based image segmentation, graph Cut, Normalized Cut (NCut) segmentation.

Among these segmentations Normalized Cut is used by most of them and it is more efficient.

Limitations:

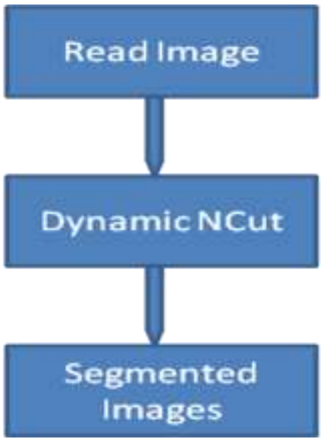
1. The number of segments should be given static before start the segmentation process.
2. Time Complexity of the Ncut is also more.

In this existing system we have to give the number of segments to divide is static.

V. PROPOSED SYSTEM

In our proposed method we used NCut segmentation and we overcome the limitations of NCut like the number of segments should be given static and the time complexity. In our method initially we have calculated number of segments should be done by using Hue-Saturation-Value (HSV) technique. We covert the particular image into graph and we calculate theeigenvalues then we partition the graph into number of segments based upon the Hue-Saturation-Value (HSV).

PROPOSED ARCHITECTURE



VI.NORMALIZED CUT

Let *G* = (*V*, *E*, *w*) be a weighted graph. Let A and B be two subsets of vertices.[2]

$$\mathrm{ncut}(A,B) = \frac{w(A,B)}{w(A,V)} + \frac{w(A,B)}{w(B,V)}$$

Let:

$$w(A,B) = \sum_{i \in A, j \in B} w_{ij}$$

$$\mathrm{nassoc}(A,B) = \frac{w(A,A)}{w(A,V)} + \frac{w(B,B)}{w(B,V)}$$

In the normalized cuts approach,for any cut $(S,\overline{S})$ in G, $\mathrm{ncut}(S,\overline{S})$ measures the similarity between different parts, and $\mathrm{nassoc}(S,\overline{S})$ measures the total similarity of vertices in the same part.

Since $\mathrm{ncut}(S,\overline{S}) = 2 - \mathrm{nassoc}(S,\overline{S})$, a cut $(S^*,\overline{S}^*)$ that minimizes $\mathrm{ncut}(S,\overline{S})$ also maximizes $\mathrm{nassoc}(S,\overline{S})$.

Computing a cut $(S^*,\overline{S}^*)$ that minimizes $\mathrm{ncut}(S,\overline{S})$ is an NP-hard problem. However, we can find in polynomial time a cut $(S,\overline{S})$ of small normalized weight $\mathrm{ncut}(S,\overline{S})$ using spectral techniques.

6.1 THE PARTITIONING ALGORITHM:

Given a set of features, set up a weighted graph $G = (V,E)$ compute the weight of each edge, and summarize the information in D and W.

1. Solve $(D - W)y = \lambda D y$ for eigenvectors with the smallest eigenvalues.
2. Use the eigenvector with the second smallest eigenvalue to bipartition the graph (e.g. grouping according to sign).

3. Decide if the current partition should be subdivided.
4. Recursively partition the segmented parts, if necessary.

WORK FLOW

VII.HUE-SATURATION VALUES

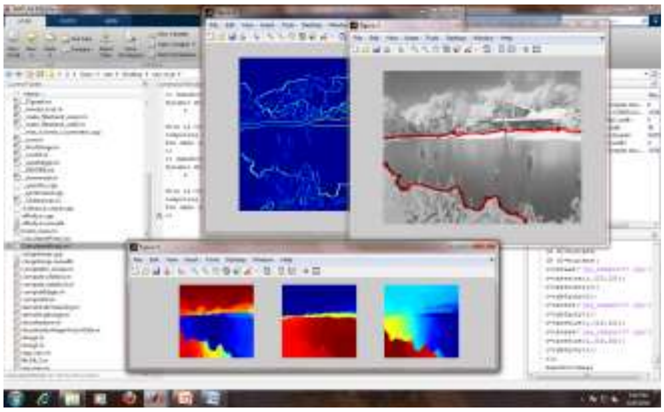
The *hue* (H) of a color refers to which pure color it resembles. All tints, tones and shades of red have the same hue. Hues are described by a number that specifies the position of the corresponding pure color on the color wheel, as a fraction between 0 and 1. Value 0 refers to red; 1/6 is yellow; 1/3 is green; and so forth around the color wheel. The *saturation* (S) of a color describes how white the color is. A pure red is fully saturated, with a saturation of 1; tints of red have saturations less than 1; and white has a saturation of 0. The *value* (V) of a color, also called its *lightness*, describes how dark the color is. A value of 0 is black, with increasing lightness moving away from black.

Fig 1.initial image

Results after segmentation
Based on hue saturation values

Fig 2.after masking

Fig 3.after segmentation



The time complexity is 5.29sec

VIII. CONCLUSION AND FUTURE WORK

In this project dynamic NCut segmentation is done based on the global features. Our experimental results depicts that the proposed method based on Hue Saturation Values gives better segmentation than the original NCut. A computational method based on this idea has been developed and applied to segmentation of brightness, color, and texture images. Results of experiments on real and synthetic images are very encouraging and illustrate that the normalized cut criterion does indeed satisfy our initial goal of extracting the “big picture” of a scene.A novel modification of the ‘Normalized Cut’ algorithm proposed here finds a better segmentation with minimum number of segments in effective run time. It has been demonstrated here that a good approximation of the Normalized Cut criterion can be made in polynomial time, and with the use of the approach proposed here, this approximation is accomplished in exactly the run time of an ordinary parametric maximal flow problem

As future work this could be extended to computer vision application such as automated image annotation and medical imaging technologies in real time environment

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