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DETAILED IMAGE SEGMENTATION USING NORMALISED CUTS AND WEIGHTED CO-EFFICIENT

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Abstract: **Image segmentation is one of the vital steps in the processing of image which includes dividing the image pixels in to salient image regions. These may be the regions corresponding to individual surfaces, objects, or natural parts of objects which could be used for object recognition, occlusion boundary estimation within motion or stereo systems, image compression or image editing. Normalized cut method of image segmentation is one of the intensively used image segmentation approach which deals with clustering a set of elements based only on the values of a similarity measure between all possible pairs of elements. Along with this method if weighted graph based analysis of clustered image is used, that would help in reducing the computational complexity and provides new vision in image segmentation. In this paper weighted graphical co-efficient and normalized cut methods are combined to get the optimal segmentation results. Once the image is segmented using normalized cut method, clusters are analyzed using weighted pixel parameters and by taking their co- efficient into consideration.**

Keywords- **Image segmentation; Normalized cut method, Image clustering**

1. INTRODUCTION

Image segmentation is an important process of image analysis. It can be defined as a process of partitioning a digital image into disjoint sub-regions of similarity. Many theories and methods have been proposed and applied to image segmentation. Two main segmentation approaches can be grouped for segmentation techniques, local features based segmentation and global features based segmentation approach. Local features based approach uses local information for particular sets of pixels or surrounding

pixels with central pixel in it. Such segmentation method has drawbacks such as it solely relies on local calculations of the particular set of pixels. The boundary identifiers are not susceptible enough to detect critical edges of objects in an image. The

misdetection of edges will lead to the segmentation results where there is no guarantee for complete closed outline contours. But, it is still difficult to accurately segment an arbitrary image by any method alone. Generally the image is mapped into a weighted undirected graph where the pixels are considered as vertexes and the similarity between the visual properties (e.g. gray-level intensity, colour or texture) at each pair of neighbouring pixels is assigned as the respective edge weight. Therefore the image segmentation can be obtained by cutting or reducing the graph with a minimum cut criteria. So, the research on the image segmentation based on graph theory has not only important, meaning but wide perspective of application. Some of the image segmentation methods with graph theory are normalized cut method [15], minimum cut method [13], min-max cut method [11], average cut method [14] and ratio cut method [12]. And normalized cut method is one where perceptual image grouping was done based on global features. In global features based Image segmentation, an image should be viewed globally by simply indentifying the similarity and dissimilarity regions in an image. Image pixels that share common features such as brightness or colour are grouped as one region which indicates that they belong to same object. One of the global features based image segmentation method is graph partitioning method by simply representing an image as a graph that can be partitioned into meaningful segments. With this method, distinctive features between regions are clear enough to enable the formation of closed contours of regions. This has the advantage over other methods for its normalized segmentation criterion. In this paper we present a novel framework for Image segmentation combining the advantages of Normalized Cut method and Markov Random Field [10] for selecting both local and global features.

2. RELATED WORKS

There are many image partitioning methods which divide image into subsets. But selecting right partition is a challenging task as expressed in [7]. This also shows us that both structure and node attributes are important to categorize the image contents. Efficient Image categorization which combines both structure and node attributes can be achieved by graph cut method as explained in [8]. In [11] Bayesian estimation is used in a multi scale setup where the MAP of number of regions, the data partition and the parameter vectors that describe the probability densities of the regions are computed. In recent days, dividing the process of Image segmentation into different stages is gaining the importance, since it reduces the complexity involved in single stage segmentation method. For multistage image segmentation, the texture features are modelled by symmetric alpha-stable (SalphaS) distributions [12].

Many algorithms have been proposed and implemented for weighted graphs, like [13] where in the Hartuv and Shamirpsila's clustering algorithm for similarity graph is extended to the weighted similarity graph. In spite of the advantages like low polynomial complexity, automatically determining the number of clusters, it is computationally expensive, because it requires the repeated evaluation for each edge in the system. Also by using different clustering criteria results may vary greatly [14], these could be the reasons for not concentrating on the clustering methods to segment the Image in this paper.

In [15], Pattern growth method to mine closed frequent pattern graphs are proposed. It incorporates the closure property with weight constrains to effectively reduce the search space and extracts the lossless patterns from graph. As per [16] the popular normalized cuts image segmentation method is improved with modifications on its graph structure. With intention of reducing the overall complexity of the algorithm, the image is represented by a weighted undirected graph, whose nodes correspond to over-segmented regions, instead of pixels. Random fields are also incorporated for the selection of graph structure but these rely on the difference in the pixel neighbourhood [17]. The segmentation is achieved by classifying pixels into different classes. All these classes can be represented by multivariate Gaussian distributions.

3. WEIGHTED GRAPH BASED PRE-PROCESSING

Normalised cut is proved to be NP-hard problem; the solution of the problem becomes extremely complex when number of nodes in the graph increases and the calculation of the problem become large.

Therefore, by taking the advantages of the weighted graph segmentation and the normalized cut (Ncut) partitioning methods, the proposed algorithm pre-processes an image by using the weighted graph algorithm to form segmented regions, using region nodes instead of these regions we formulate the Ncut method for region nodes clustering. Ncut method brings large computational complexity since it is applied directly to image pixels. However, this method reduces it because the number of image region nodes is much smaller than that of the pixels.

As a pre-processing step, in weighted graph co-efficient method, similarity of a pixel with its neighbourhood is taken as the weighted co-efficient and each pixel under consideration acts as a node, thus forming a weighted graph of image region, which acts as a input to the N-cut method. Each Image region so formed would be considered as a node while applying the N-cut method.

Probabilistic relationship between the pixels and their neighbourhood can be estimated by understanding the concept of random field in general and Markov Random Field in particular.

Random Fields on graphs:

Consider a collection of random variables x = (x1; x2…, xN) with associated joint probability distribution p(x).Let A, B, C be three disjoint subsets of V. Let xA denote the collection of random variables in A.
Then Conditional independence A || B | C can be modelled as:

A || B | C <=> p(xA, xB|xC) = p(xA|xC)p(xB|xC) …1

Markov random field:

This is an undirected graphical model in which each node corresponds to a random variable or a collection of random variables, and the edges identify conditional dependencies.
There are two types of Markovianity defined: Pair wise, Local and Global Markovianity.

Pair wise Markovianity:

$(ni, nj) \notin \varepsilon = \rightarrow x_i$ and x_j are independent when conditioned on all other variables

p(xi,xj |X\{$_{I,}$ j} = p(xi|X\{$_{i,}$ j})p(xj |X\{i, j}) …2

Local Markovianity:

When the neighbourhood of a variable is defined, and when it is independent on the rest of the variables.

p (xi|Xγ\{i}) = p(xi|XN(i)) …3

Global Markovianity:

Let A, B, C be the three disjoint subsets of γ. If C separates A from B

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$P(X_A,X_B,X_C)=P(X_A|X_C)P(X_B|X_C)$, then P(.) is global Markov process w.r.t ς.

Based on the probability distribution model and Markovianity, as per the Hammersley Clifford theorem, "probability distribution that has a positive mass or density satisfies one of the Markov properties with respect to an undirected graph G if and only if it is a Gibbs random field, that is, its density can be factorized over the cliques (or complete subgraphs) of the graph." Hammersley Clifford theorem can be mathematically defined as below:

Consider a random field x on a graph G, such that p(x) > 0. Let C denote the set of all maximal cliques of the graph. If the field has the local Markov property, then p(x) can be written as a Gibbs distribution:

where Z, the normalizing constant, is called the partition function; $V_c(xC)$ are the clique potentials derived from the subgraphs or pixel relationships, If p(x) can be written in Gibbs form for the cliques of some graph, then it has the global Markov property. Fundamental consequence of the theorem is every Markov random field can be specified via clique potentials. This will help us in the fact that same can be used to identify the node potential and node relationship.

The k neighbourhood systems for the variable under consideration can be calculated by

Where 'I' vary from 1 to m and 'j' varies from 1 to n.

Clique potential Vc for each variable can be calculated as

As long as .

All these potentials are grouped together as a matrix CP. Where CP (i, j) represents a value of probability corresponding to the neighbourhood.

In total, the density of Gaussian MRF can be derived from 6 as

(ii) Normalized Cut Method:

The set of points in an arbitrary feature space can be described as a weighted undirected graph G= (V, E), where the nodes of the graph are the points in the feature space, and an edge is formed between every pair of nodes. The weight on each edge, W(i, j), is a function of the similarity between nodes i and j. A graph G = (V, E) can be partitioned into two disjoint sets, A , B , AUB=V ,AB=Φ, we expected that the intra-group similarity is high and the intergroup similarity is low. In graph theoretic language, a mathematical formulation of a cut is [3]

w(u,v) …8

The Ncut is

…9

In this paper, we will use this normalized cut (N cut) as the partition criterion. Where Assoc(A,V)= w(u,v) is the total connection from nodes in A to all nodes in the graph and Assoc(B,V)= , w(u,v) is the connections from node B to all the nodes. Best image segmentation results can be achieved once the minimum value of N cut is obtained.

4. IMPLEMENTATION AND RESULTS:

To integrate the proposed method, first the weight on each edge is calculated using the best available condition of clique potential obtained from the MRF. Vc minimum is found out from each set of neighborhoods and then carried out into normalize cut process. Selection of a particular clique will always lead into a disjoint set so Cut (A, B)= W(u,v) deduce to a minimum criterion. Computer with a 3.00-GHz Pentium CPU and 2G memory is applied to carry out the computation of the proposed method. Two block processing is done on the image which in first step decides the neighbour and second step applies the N-CUT Method. Usually N-CUT method itself takes 40-50s for classification. Added to this will be the total time for segmentation.

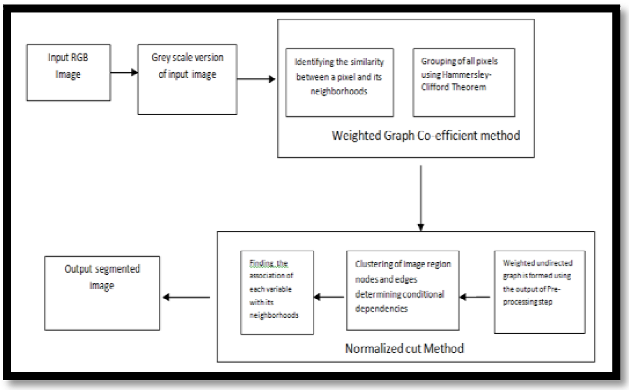

Fig 1: Block Diagram explaining the Algorithm

Fig 2: Clockwise from top left images: Birds1, Birds2, Game1 and Flower1.

Table 1: Compared computational cost between the proposed method and the Normalized cut method.

Sl. No	Image Name	N-cut Algorithm	Proposed Algorithm
1	Birds 1	9.47	8.56
2	Birds 2	3.76	3.47
3	Game1	8.67	8.33
4	Flower 1	10.3	9.8

CONCLUSION

Graphical models study probability distributions whose conditional dependencies arise out of specified graph structures. Markov random field is an undirected graphical model with special factorization properties. 2-D MRFs have been widely used as priors in image processing problems, choice of potential functions lead to different optimization problems. To optimize the performance of normalized cuts algorithm which is considered a NP-hard problem an alternative approach should be implemented to help reducing unnecessary image segmentation instead of performing segmentation on whole image alone. Segmentation on image, part by part individually also helps to speed up the computation time of similarity measurement in this method.

This novel image segmentation algorithm employs the advantages of both the Normalized Cuts algorithm of graph partitioning and weighted graph coefficients method for solving the perceptual grouping problem and the multi scale graph decomposition for obtaining image features. This technique can adaptively fine tune parameters such as the image cell size and numbers of image cells according to the image content, foreground area that covers more than background area, the number of image cells can be such a way it is not many to reduce the tendency of waste in computation time in the proposed algorithm. Through this method, we can greatly reduce the time while achieving the required quality. It finds an approximate solution to normalized cuts measure in time that is linear in the size of the image with only a few number of operations per pixel. Future research directions include the use of various statistics to obtain segmentation based on detailed information, improving the similarity of the interpolations to produce smoother boundaries of segments, and combining the segmentation process with curve completion algorithms and top-down analysis of the image. The effectiveness and robustness of the proposed algorithm have verified by some experimental results to express an improved performance compared to the existing graph based segmentation methods.

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