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Image Segmentation Using Pairwise Correlation Clustering

H. Umamaheswari, S. Saraswathi, M.E,
Electronics and Communication Engineering Mahendra Engineering College Thiruchengode, Namakkal
Assistant Professor, Mahendra Engineering College Thiruchengode, Namakkal

Abstract
A pairwise hypergraph based image segmentation framework is formulated in a supervised manner for various images. The image segmentation is to infer the edge label over the pairwise hypergraph by maximizing the normalized cuts. Correlation clustering which is a graph partitioning algorithm, was shown to be effective in a number of applications such as identification, clustering of documents and image segmentation.The partitioning result is derived from a algorithm to partition a pairwise graph into disjoint groups of coherent nodes. In the pairwise correlation clustering, the pairwise graph which is used in the correlation clustering is generalized to a superpixel graph where a node corresponds to a superpixel and a link between adjacent superpixels corresponds to an edge. This pairwise correlation clustering also considers the feature vector which extracts several visual cues from a superpixel, including brightness, color, texture, and shape. Significant progress in clustering has been achieved by algorithms that are based on pairwise affinities between the datasets. The experimental results are shown by calculating the typical cut and inference in an undirected graphical model and datasets.
Keywords- Image segmentation, correlation clustering, superpixel

I. INTRODUCTION

Image segmentation is the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and/or change the representation of an image to analyze more easier and something that is meaningful. Image segmentation is typically used to locate the lines and curves in boundaries and also to locate objects in images. Then image segmentation may also be defined in such a way that the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments where the entire image is covered collectively, or a set of contours where the image is extracted which can be seen in edge detection. Some characteristic or computed property of pixels, such as color, intensity, or texture are similar with respect to each region, whereas the pixels which have same characteristics differs from the adjacent regions. When applied to medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes.

Several general purpose algorithms and techniques have been developed for image segmentation. These algorithms and techniques must be typically combined with a domain's specific knowledge in order to effectively solve the domain's segmentation problems.

1.1 Clustering methods

The K-means algorithm is an iterative technique that is used to partition an image into K-clusters.The basic slgorithm is

1. Pick K cluster centers, either randomly or based on some heuristic.
2. Assign each pixel in the image to the cluster that maximizes the distance between the pixel and the cluster center.
3. Re-compute the cluster centers by averaging all of the pixels in the cluster.
4. Repeat steps 2 and 3 until convergence is attained (i.e. no pixels change clusters).

In this case, absolute difference between a pixel and a cluster center or the distance is squared. This absolute difference is typically based on pixel color, intensity, texture, and location, or a weighted combination of these factors. Manually, randomly, or by a heuristically this K can be selected. This algorithm is guaranteed to converge, but it may not return the optimal solution so it is found that the quality of the solution depends on the initial set of clusters and the value of *K*.

1.2 Histogram-based methods

Histogram-based methods are very efficient compared to other image segmentation methods because they typically require only one pass through the pixels.The peaks and valleys in the histogram are used to locate the clusters in the image, where as the histogram is also computed in the image by considering all the pixels. To measure color or intensity also this histogram is used. The histogram-seeking method is also used to cluster the image in order to divide them into smaller clusters. No more clusters are formed, because by repeating this operation until the smaller clusters being taken.

1.3 Edge detection

Edge detection is a well-developed field on its own within image processing.Since there is often a sharp adjustment in intensity at the region boundaries, where the edges and the boundaries in the region are closely related. Therefore, the edge detection techniques have been used as the base of another segmentation technique. In this edge detection, the edges being identified are often disconnected. The closed region boundaries are needed in order to segment an object from an image. The boundaries between such objects or spatial-taxons have desired edges.

Spatial-taxons are information granules consisting of a crisp pixel region, where these pixel regions are stationed at abstraction levels within a hierarchical nested scene architecture.

II. LITERATURE SURVEY

This paper addresses the problem of segmenting an image into regions. The boundary between two regions using a graph-based representation of the image is predicated for measuring the evidence.Based on this predicate an efficient segmentation algorithm is developed, and shows that this algorithm makes greedy decisions where it produces segmentations that satisfy global properties. An algorithm to image segmentation is applied using two different kinds of local neighbourhoods to illustrate the results with both real and synthetic images and also to construct the graph.The algorithm nearly runs faster in practice ans also in time linear in the number of graph edges. The characteristic of the method is more important because its ability is to preserve detail in low-variability image regions while ignoring detail in high-variability regions.

A wide range of computational vision problems could in principle make good use of segmented images, where it is computable with its reliability and in efficient using such segmentations. Consider an instance that the intermediate-level vision problems such as stereo and motion estimation require an appropriate region of support for correspondence operations. The non-uniform regions of support can be identified spatially using segmentation techniques. Higher-level problems such as recognition and image indexing can also make use of segmentation results in matching, to address problems such as ground separation and recognition by parts.

The goal is to develop computational approaches to image segmentation that are broadly useful, much in the way that other low-level techniques such as edge detection are used in a wide range of computer vision tasks. A novel approach for solving the perceptual grouping problem in vision is mainly focusing on local features and their consistencies in the image data, where our approach aims at extracting the global impression of an image. In image segmentation mainly a graph partitioning problem arises so to segment the graph and also to recover that a novel global criterion, the normalized cut is being proposed. The normalized cut which is proposed above, measures both the total dissimilarity between the different groups as well as the total similarity within the groups. We show that an efficient computational technique based on a generalized eigenvalue problem can be used to optimize this criterion.

III. RELATED WORK

3.1 Block diagram

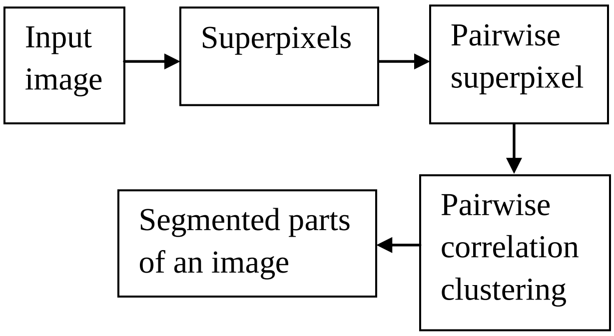


Fig 3.1 General block diagram

The proposed image segmentation is based on superpixels which are small coherent regions preserving almost all boundaries between different regions. This is an advantage since superpixels significantly reduce computational cost and allow feature extraction to be conducted from a larger coherent region. Both the pairwise and higher-order correlation clustering merges superpixels into disjoint coherent regions over a superpixel graph. Therefore, the proposed correlation clustering is not a replacement to existing superpixel algorithms, and performances might be influenced by baseline superpixels.

The group of pixels which have similar characteristics. The surface layout recovering helps computers understand the intricate information in an image by assigning local segments to different geometric classes. It is widely used in various computer vision applications and also it greatly reduces the complexity of the following-up image processing.

The regions are selected beforehand and then an energy function is defined over them. The regions which is used in two step process suffers from the following deficiencies: (i) the regions may not match the boundaries of the scene entities, thereby introducing errors; and (ii) It may not be suitable for the task at hand as the regions are obtained without any knowledge of the energy function.The segments are merged and intersected in order to construct the dictionary where it is obtained from multiple bottom-up over segmentations.

$$y_{jk} = \begin{cases} 1 \text{ ,if j and k belong to the same region} \\ 0 \text{ ,otherwise .} \end{cases}$$

A discriminant function for x and y label of all edges is defined over an image where as,

$$F (x, y ; w) = \sum_{(j\ ,k\ )\in\varepsilon} Sim_w(x\ ,j,k)y_{jk}$$
$$= \sum_{(j,k)\in\varepsilon}(w,\emptyset_{jk}\ (x))\ y_{jk}$$

Most methods for object class segmentation are formulated as a labelling problem over a single choice of quantization of an image space pixels, or group of segments. Each quantisation has its fair share of pros and cons which is well known already; and the existence of a common optimal quantisation level suitable for all object categories is highly unlikely. Motivated by this observation, that they allows integration of features computed at different levels of the quantization hierarchy to propose a hierarchical random field model. MAP inference in this model can be performed efficiently using powerful graph cut based move making algorithms. The flexibility and generality of our framework allowed us to propose and use novel pixel and segment based potential functions and achieve state-of-the-art results on some of the most challenging data sets for object class segmentation. It is believed that the use of the hierarchical CRF will yield similar improvements for other labelling problems.

3.2 LP Relaxation for Pairwise Correlation Clustering

$$argmax = \sum_{(j,k)\in\varepsilon}^{0} (\mathrm{W}, \mathrm{Q}_{jk}\ (\mathrm{x})_{jk}$$

High-level, or holistic, scene understanding involves reasoning about the 3D relationships between the objects and the regions. This requires a representation above the level of pixels that can be endowed with high-level attributes such as class of object/region, its orientation, and location within the scene. Towards this goal, it propose a region-based model which combines appearance and scene geometry to automatically decompose a scene into semantically meaningful regions. It is defined in terms of a unified energy function over scene appearance and structure. An effective inference technique is proposed for optimizing this energy function and it is showed that how it could be learned from data. This results compete with the geometric reasoning techniques and state-of-the-art multi-class image segmentation.

This shows that hypergraphs provide a more relevant representation of images than the ones based on pairwise relationships, i.e. graph-based representations, with comparison to the various algorithm. They have also showed that a combination of spectral decomposition methods and the multilevel paradigm outperforms the pure heuristic multilevel hypergraph partitioning algorithm. The representation is unrelevant for highly textured images as demonstrated. This establish the efficiency of the filtering algorithm in practical by two ways.

First,,it shows that the algorithm runs faster as the separation between clusters increases where it presents a data-sensitive analysis of the algorithm's running time. Second, present a number of empirical studies on both the real data sets from applications in color quantization, data compression, and image segmentation and on synthetically generated data. The algorithm is easy to implement and only requires that a kd-tree be built once for the given data points. Efficiency is achieved because the data points do not vary throughout the computation process and this data structure does not need to be recomputed at each stage.

3.3 Pairwise feature vector

In order to consider the problem of estimating the depth of each pixel in a scene from a single monocular image. First perform a semantic segmentation of the scene and use the semantic labels to guide the 3D reconstruction in traditional approach which attempts to map from appearance features to depth directly. This traditional approach provides several advantages by knowing the semantic class of a region or pixel, where the depth and geometry constraints can be easily enforced . In addition, depth can be more readily predicted by measuring the difference in appearance with respect to a given semantic class.

$$\emptyset_{eh} = [\ \emptyset_{eh}^{va}\ ;\ \emptyset_{eh}^{e}\ ;\ \emptyset_{eh}^{tm}\ ;\ 1\ ].$$

Define a predicate for measuring the evidence for a boundary between two regions using a graph-based representation of the image and in this predicate it develops an efficient segmentation algorithm, and show that although this algorithm makes greedy decisions it produces segmentations that satisfy global properties. The algorithm which is applied to image segmentation, illustrates the results with both real and synthetic images using two different kinds of local neighborhoods in constructing the graph.

An important characteristic of the method is its ability to preserve detail in low-variability image regions while ignoring detail in high-variability regions. The pairwise region comparison predicate considers the minimum weight edge between two regions in measuring the difference between them. Thus our algorithm will merge two regions even if there is a single low weight edge between them. This is not as much of a problem as it might first appear, in part because the minimum spanning tree edges of each component is compared with its edge weight.

3.4 Comparison with Related Eigenvector-Based Methods

The normalized cut formulation has a certain resemblance to the standard spectral graph partitioning, as well as average association formulation and average cut. All three of these algorithms can be reduced to solving certain eigen value systems. This fig summarizes the relationship between these three algorithms. On the one hand, the normalized association and the average association are trying to find tight clusters in the graph, on the another hand, both the normalized cut and the average cut algorithm are trying to find a balanced partition of a weighted graph.

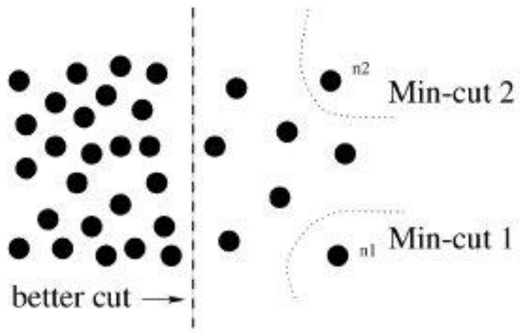


Fig.3.1 A case where minimum cut gives a bad partition

Since the normalized association is exactly n cut, the normalized cut value, the normalized cut formulation seeks a balance between the goal of clustering and segmentation. The normalized cut vector can be approximated with the generalized eigenvector where it not seen surprisingly. It can be seen that the average association, has a bias for finding tight clusters by judging these three grouping criteria from the discrete formulations.

Table No.3.1 Relationship between normalized cut and other eigenvector-based partitioning techniques. When compared to the average cut and association formulation.

Parameters	Average Association	Normalized Cut	Average Cut
Discrete Formulation	$\frac{asso\,(A,A)}{\lvert A\rvert} + \frac{asso\,(B,B)}{\lvert B\rvert}$	$\frac{cut(A,B)}{asso(A,V)} + \frac{cut(A,B)}{asso(B,V)}$ or 2-($\frac{asso\,(B,B)}{asso\,(A,V)} + \frac{asso\,(B,B)}{asso\,(B,V)}$)	$\frac{cut\,(A,A)}{\lvert A\rvert} + \frac{cut\,(B,B)}{\lvert B\rvert}$
Continuous Solution	$W_X = \lambda X$	(D-W)X $= \lambda DX$ Or $W_X =$ (1-λ)DX	(D-W)X $=\lambda X$

Therefore, it runs the risk of becoming too greedy in finding small, but tight, clusters in the data. This might be perfect for data that are Gaussian distributed. However, this bias in grouping will have undesired consequences for typical data in the real world that are more likely to be made up of a mixture of various different types of distributions. One cannot ensure the two partitions computed will have tight within-group similarity. This becomes particularly problematic if there are several possible partitions all with similar average cut values or there is an dissimilarity among the different groups varies from one to another.

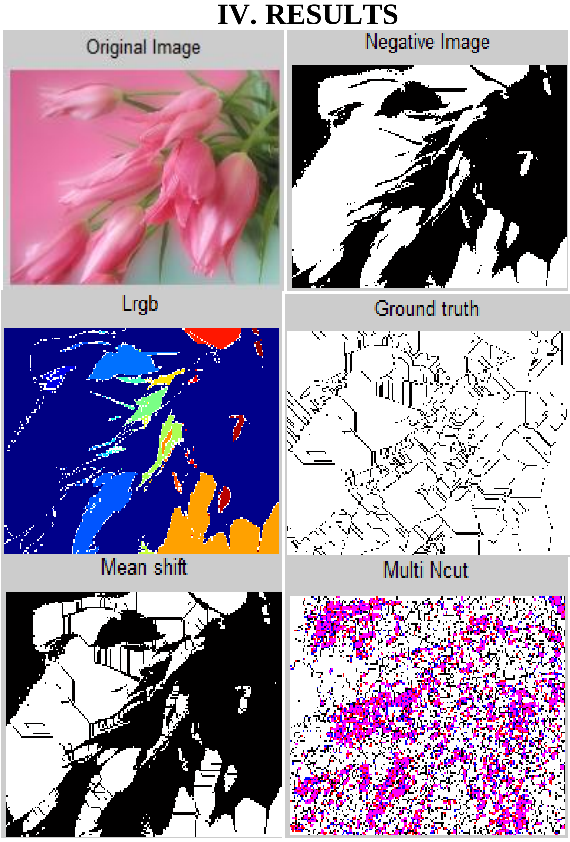
Each data point is taken as a node in the graph and the weighted graph edge connecting two points is defined to be inversely proportional to the distance between two nodes.

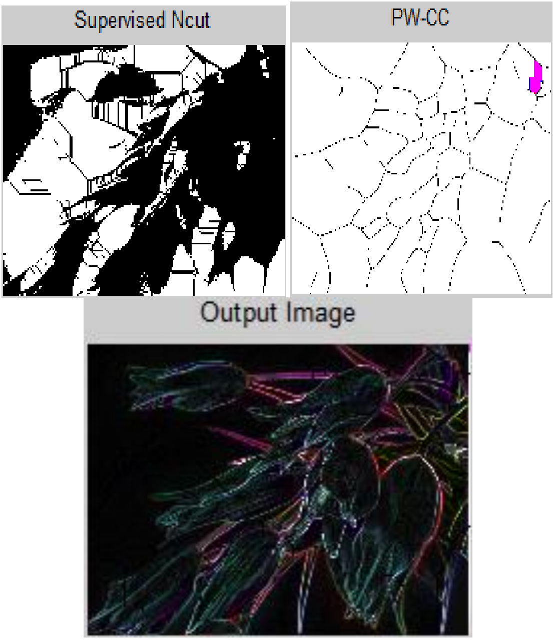
3.5 Pairwise correlation clustering over the superpixel graph

Define a pairwise undirected graph where a node corresponds to a superpixel and a link between adjacent superpixels corresponds to an edge. Note that the discriminant function is assumed to be linear in both the parameter vector and the joint feature map is a pairwise feature vector which reflects the correspondence between the superpixels.

An image segmentation is to infer the edge labelover the pairwise superpixel that corresponds to a valid segmentation, the so called multicut polytope.

IV. RESULTS





V. CONCLUSION

The algorithms for image segmentation and also the various cuts such as normalized cuts, average cuts, average association and m-cuts for the implementation of pairwise correlation is studied. Then the correlation clustering which is a graph partioning algorithm has also been studied in order to obtain the efficient datasets for the higher correlation clustering and the pairwise correlation clustering.

VI. FUTURE WORK

The performance measures such as probabilistic Rand index , segmentation covering, variation of information, and boundary displacement error will be calculated with respect to various data sets. The various data sets are also being compared along with the feature vectors in order to obtain the pairwise graph for future enhancement.

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