ISSN 2229-5518

Image Classification Using Segmentation Graph Kernels

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Abstract— Introducing a multiregion graph cut image partitioning through kernel mapping of the image data. The proposed functional contains two terms: an original kernel-induced term which evaluates the deviation of the mapped image data within each region from the piecewise constant model and a regularization term expressed as a function of the region indices. Using a common kernel function, the objective functional minimization is carried out by iterations of two consecutive steps: 1) minimization with respect to the image segmentation by graph cuts 2) minimization with respect to the regions parameters via fixed point computation

Index Terms— Graph cuts,Pixel label,Segmentation,Graph kernels,Pixel ratio,Optimization,Region parameters

1 Introduction

An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows. In a (8-bit) grayscale image each picture element has an assigned intensity that ranges from 0 to 255. A grey scale image is what people normally call a black and white image, but the name emphasizes that such an image will also include many shades of grey.

A normal grayscale image has 8 bit colour depth = 256 grayscales. A "true colour" image has 24 bit colour depth = 8 x 8 x 8 bits = 256 x 256 x 256 colours = ~16 million colours. Some grayscale images have more grayscales, for instance 16 bit = 65536 grayscales. In principle three grayscale images can be combined to form an image with 281,474,976,710,656 grayscales.

When you open the document, select "Page Layout" from the "View" menu in the menu bar (View | Page Layout), which allows you to see the footnotes. Then type over sections of the document or cut and paste from another document and There are two general groups of 'images': vector graphics (or line art) and bitmaps (pixel-based or 'images'). Some of the most common file formats are:

GIF — an 8-bit (256 colour), non-destructively compressed bitmap format. Mostly used for web. Has several sub-standards one of which is the animated GIF.

JPEG — a very efficient (i.e. much information per byte) destructively compressed 24 bit (16 million colours) bitmap format. Widely used, especially for web and Internet (bandwidth-limited).

TIFF — the standard 24 bit publication bitmap format. Compresses non-destructively with, for instance, Lempel-Ziv-Welch (LZW) compression.

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PS — Postscript, a standard vector format. Has numerous sub-standards and can be difficult to transport across platforms and operating systems.

PSD – a dedicated Photoshop format that keeps all the information in an image including all the layers. For science communication, the two main colour spaces are RGB and CMYK. The RGB colour model relates very closely to the way we perceive colour with the **r**, **g** and **b** receptors in our retinas. RGB uses additive colour mixing and is the basic colour model used in television or any other medium that projects colour with light. It is the basic colour model used in computers and for web graphics, but it cannot be used for print production.

The secondary colours of RGB – cyan, magenta, and yellow – are formed by mixing two of the primary colours (red, green or blue) and excluding the third colour. Red and green combine to make yellow, green and blue to make cyan, and blue and red form magenta. The combination of red, green, and blue in full intensity makes white. In Photoshop using the "screen" mode for the different layers in an image will make the intensities mix together according to the additive colour mixing model. This is analogous to stacking slide images on top of each other and shining light through them.

CMYK

The 4-colour CMYK model used in printing lays down overlapping layers of varying percentages of transparent cyan (C), magenta (M) and yellow (Y) inks. In addition a layer of black (K) ink can be added. The CMYK model uses the subtractive colour model.

Gamut

The range, or gamut, of human colour perception is quite large. The two colour spaces discussed here span only a fraction of the colours we can see. Furthermore the two spaces do not have the same gamut, meaning that converting from one colour space to the other may cause problems for colours in the outer regions of the gamuts.

Astronomical images

Images of astronomical objects are usually taken with electronic detectors such as a CCD (Charge Coupled Device). Similar detectors are found in normal digital cameras. Telescope images are nearly always grayscale, but nevertheless contain some colour information. An astronomical image may be taken through a colour filter. Different detectors and telescopes also usually have different sensitivities to different colours (wavelengths).

Filters

Filters can either be broad-band (**W**ide) or narrow-band (**N**arrow). A broad-band filter lets a wide range of colours through, for instance the entire green or red area of the spectrum. A narrow-band filter typically only lets a small wavelength span through, thus effectively restricting the transmitted radiation to that coming from a given atomic transition, allowing astronomers to investigate individual atomic processes in the object.

Natural colour images

It is possible to create colour images that are close to "true-colour" if three wide band exposures exist, and if the filters are close to the r, g and b receptors in our eyes. Images that approximate what a fictitious space traveler would see if he or she actually travelled to the object are called "natural colour" images. To make a natural colour image the order of the colours assigned to the different exposures should be in "chromatic order", i.e. the lowest wavelength should be given a blue hue, the middle wavelength a green hue and the highest wavelength should be red.

Representative colour images

If one or more of the images in a data set is taken through a filter that allows radiation that lies outside the human vision span to pass i.e. it records radiation invisible to us, it is of course not possible to make a natural colour image. But it is still possible to make a colour image that shows important information about the object. This type of image is called a representative colour image. Normally one would assign colours to these exposures in chromatic order with blue assigned to the shortest wavelength, and red to the longest. In this way it is possible to make colour images from electromagnetic radiation far from the human vision area, for example x-rays.

Stretch function

One particularly important aspect of image processing is the choice of the best stretch function. A logarithmic representation of the pixel values tends to suppress the bright parts of the image, i.e. the stars, and to enhance the fainter part, e.g. nebulosity. This can be desirable if the 'faint stuff' needs 'a boost', but a logarithmic stretch function can also reduce the contrast in an image, producing a lower dynamic range.

1.1 Problem Definition

The purpose of multiregional image segmentation is to divide an image into regions answering a given description.Continuous formulations view images as continuous functions over a continuous domain.Unsupervised graph cut methods, which do not require user intervention, have used the piecewise model, or its Gaussian generalization, because the data term can be written in the form required by the graph cut algorithm.Graph cut image segmentation commonly stated as a maximum a posteriori *(MAP)* estimation problemIntroduce the kernel-induced data term in the graph cut segmentation functional. It also gives functional optimization equations and the ensuing algorithm.

1.2 Existing System

In existing system the parameter learning and the segmentation process are only loosely coupled in the sense that they do not result from the objective function optimization. Interactive graph cut methods have used models more general than the Gaussian by adding a process to learn the region parameters at any step of the graph cut segmentation process. These parameters become part of the data at each step. However, the parameter learning and the segmentation process are only loosely coupled in the sense that they do not result from the objective function optimization.

1.3 Drawbacks of Existing System

The idea of matching graphs for the purpose of image classification has a long history in computer vision. However, the general *graph matching* problem is especially hard as most of the simple operations which are simple on strings (such as matching and edit distances) are NP-hard for general undirected graphs. While exact graph matching is unrealistic in our context, inexact graph matching is NP-hard and sub graph matching is NP-complete. Hence most work so far has focused on finding ingenious approximate solutions to this challenging problem. An interesting line of research consists in overcoming graph matching problems by projecting graphs on strings by the so-called seriation procedure, and then use string edit distance as a proxy to graph edit distance. So to avoid these hardness problems kernels can be used for image classification. In this paper tree walk kernels are used for segmentation.

1.4 Proposed System

Investigation of multiregional graph cut image segmentation in a kernel-induced space. The proposed method consists of minimizing a functional containing an original data term

ISSN 2229-5518

which references the image data transformed via a kernel function. The optimization algorithm iterated two consecutive steps: 1.graph cut optimization 2.fixed point iterations for updating the regions parameters. A quantitative and comparative performance study over a very large number of experiments on synthetic images illustrated the flexibility and effectiveness of the proposed method. The purpose of segmentation is to divide an image into regions answering a given description. Existing systems have focused on variational formulations because they result in the most effective algorithms. Variational formulations seek an image partition which minimizes an objective functional containing terms that embed descriptions of its regions and their boundaries. The literature abounds of both continuous and discrete formulations. Minimization by graph cuts of objective functionals with a piecewise constant data term produce nearly global optima and, therefore, are less sensitive to initialization. In our proposed system we aim the following two main steps,

1) Minimization with respect to the image segmentation by graph cuts.

2) Minimization with respect to the regions parameters via fixed point computation.

1.5 Objective

Use a common kernel function, and to verify the effectiveness of the method by a quantitative and comparative performance evaluation over a large number of experiments on synthetic images and to improve the segmentation accuracy and flexibility

2.LITERATURE SURVEY

Normalized Cuts and Image Segmentation [1] proposed a novel approach for solving the perceptual grouping problem in vision. Rather than focusing on local features and their consistencies in the image data, the approach aims at extracting the global impression of an image. Image segmentation is a graph partitioning problem and proposes a novel global criterion, the normalized cut, for segmenting the graph. The normalized cut criterion measures both the total dissimilarity between the different groups as well as the total similarity within the groups. This shows an efficient computational technique based on a generalized eigenvalue problem that can be used to optimize this criterion. This approach is applied for segmenting static images, as well as motion sequences, and found the results to be very encouraging.

A grouping algorithm based on the view that perceptual grouping should be a process that aims to extract global impressions of a scene and provides a hierarchical description of it. By treating the grouping problem as a graph partitioning problem, here proposed the normalized cut criteria for segmenting the graph. Normalized cut is an unbiased measure of disassociation between subgroups of a graph and it has the nice property that minimizing normalized cut leads directly to maximizing the normalized association, which is an unbiased measure for total association within the subgroups. In finding an efficient algorithm for computing the minimum normalized cut, a generalized eigenvalue system provides a real valued solution to the problem. 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.

Fast Approximate Minimization by energy efficient graph Cuts [2] Many tasks in computer vision involve assigning a label (such as disparity) to every pixel. A common constraint is that the labels should vary smoothly almost everywhere while preserving sharp discontinuities that may exist, e.g., at object boundaries. These tasks are naturally stated in terms of energy minimization. In this paper, a wide class of energies with various smoothness constraints is considered. Global minimization of these energy functions is NP-hard even in the simplest discontinuity-preserving case. Therefore, the focus is on efficient approximation algorithms. This presents two algorithms based on graph cuts that efficiently find a local minimum with respect to two types of large moves, namely expansion moves and swap moves. These moves can simultaneously change the labels of arbitrarily large sets of pixels. In contrast, many standard algorithms (including simulated annealing) use small moves where only one pixel changes its label at a time. The expansion algorithm finds a labeling within a known factor of the global minimum, while the swap algorithm handles more general energy functions. Both of these algorithms allow important cases of discontinuity preserving energies. The approach for image restoration, stereo and motion was effective and achieved about 98 percent accuracy.

Here considered a wide class of energy functions with various discontinuity preserving smoothness constraints. While it is NP-hard to compute the exact minimum, developed two algorithms based on graph cuts that efficiently find a local minimum with respect to two large moves, namely, -expansion moves and --swap moves. Our –expansion algorithm finds a labeling within a known factor of the global minimum, while our --swap algorithm handles more general energy functions. The combinatorial optimization techniques, such as graph cuts, will prove to be powerful tools for solving many computer vision problems.

An Experimental comparison of Min-cut /Max-Flow Algorithms for Energy minimization in Vision [3] emerged as an increasingly useful tool for exact or approximate energy minimization in low-level vision. The combinatorial optimization literature provides many min-cut/max-flow algorithms with different polynomial time complexity. Their practical efficiency, however, has to date been studied mainly outside the scope of computer vision. The goal of this paper is to provide an experimental comparison of the efficiency of min-cut/max flow algorithms for applications in vision. Here compared the running times of several standard algorithms, as well as a new algorithm that has been developed recently. The algorithm studied includes both Goldberg-Tarjan style "push-relabel" methods and algorithms based on Ford- Fulkerson style "augmenting paths." We benchmark these algorithms on a number of typical graphs in the contexts of image restoration, stereo, and segmentation. In many cases, the new algorithm works several times faster than any of the other methods, making near real-time performance possible. An implementation of our max-flow/min-cut algorithm is available upon request for research purposes.

Here a test is done on reasonable sample of typical vision graphs. In most examples, the new min-cut/max-flow algorithm worked 2-5 times faster than any of the other methods, including the push-relabel and the Dinic algorithms (which are known to outperform other min-cut/max-flow techniques). In some cases, the new algorithm made possible near real-time performance of the corresponding applications. More specifically, it can be concluded that our algorithm is consistently several times faster (than the second best method) in all applications where graphs are 2D grids.

Multiregion Level-Set segmentation of Synthetic Aperture Radar Images[4] investigate Synthetic Aperture Radar (SAR) image segmentation into a given but arbitrary number of gamma homogeneous regions via active contours and level sets. The segmentation of SAR images is a difficult problem due to the presence of speckle which can be modeled as strong, multiplicative noise. The proposed algorithm consists of evolving simple closed planar curves within an explicit correspondence between the interiors of curves and regions of segmentation to minimize a criterion containing a term of conformity of data to a speckle model of noise and a term of regularization. Results are shown on both synthetic and real images. Presented a curve evolution algorithm for segmenting synthetic aperture radar (SAR) image into a fixed but arbitrary number of Gamma-homogeneous regions. This algorithm consists in evolving curves in order to minimize a statistical criterion. This led to partitions of the image domain following an explicit correspondence between segmentation regions and regions enclosed by evolving curves. The algorithm was illustrated on both synthetic and real SAR images. The proposed technique can be improved by introducing a way to estimate the number of regions and can be extended to other representations of SAR images such as vector valued polar metric SAR images.

Graph cut based active contour for multiphase image Segmentation [5] presents a unified framework that unifies two basic segmentation approaches; level set methods and graph cut algorithms. A bimodal image segmentation approach have the advantages of the level set methods such as robustness to noise, blurred edges and topology changes and the advantages of graph cuts vis-a-vis global optimization and speed. The main objective in this paper is to extend our previous approach to segment n classes. The results show that our algorithm outperforms the multiphase image segmentation approach and also the segmentation algorithm is very robust to noise and topology changes and it can detect triple junctions because it maintains all the advantages of the level set formulation. The algorithms also have the advantages of graph cut optimization, and hence it is very fast and insensitive to initialization.

3 Segmentation graph kernals

3.1 Implicit mapping of image data into high dimensional feature(kernel) space

- map the image data to a predetermined very high-dimensional space via a kernel function
- Find the hyper plane that maximizes the margin between the two regions
- If data are not separable find the hyper plane that maximizes the margin.

3.2 Application of piecewise constant model

Find the regions and the constant values inside the regions for the segmentation. Set the constant values as minimization variables. Solving image segmentation in a kernel-induced space with graph cuts consists of finding the labeling which minimizes the following function and measures kernel-induced non Euclidean distances between the observations and the regions parameters

$$\mathcal{F}_K(\{\mu_l\},\lambda) = \sum_{l\in\mathcal{L}} \sum_{p\in R_l} (\phi(\mu_l) - \phi(I_p))^2 + \alpha \sum_{\{p,q\}\in\mathcal{N}} r(\lambda(p),\lambda(q)). \quad (1)$$

3.3 Evaluate the deviation of the mapped image data within each region from the piecewise constant model by an original kernel-induced term and express the regularization term as a function of the region indices.

Use the following kernel function, where " ." is the dot product in the feature space.

$$K(y,z)=\phi(y)^T.\phi(z), \qquad \forall(y,z)\in I^2 \quad (2)$$

After substituting the kernel functions we got a non-Euclidean distance measure in the original data space corresponding to the squared norm in the feature space. Simplification yields kernel induced segmentation functional term.

3.4 Minimization of objective function by using a RBF kernel function

RBF kernel function is defined as

ISSN 2229-5518

$$K(y,z)=\exp(-\|y-z\|^2 / \sigma^2) \quad (3)$$

The RBF kernel has been prevalent in pattern data clustering. With this kernel, the necessary condition for a minimum of the segmentation functional, with respect to region parameter by the following fixed point equation

$$\mu_K - f_{R_K}(\mu_k)=0,\ \ k \in L \quad (4)$$

3.5 Minimization with respect to the regions parameters via fixed point computation.

This step consists of fixing the labeling (or the image partition) and optimizing with respect to statistical regions parameters via fixed point computation.

3.6 Minimization with respect to the image segmentation by graph cuts.

This step consists of finding the optimal labeling/partition of the image, given region parameters provided by the previous step, via graph cut iterations. The algorithm iterates these two steps until convergence. A cut is a set of edges the removal of which separates the terminals into two induced subgraphs.This cut is minimal in the sense that none of its subsets separates the terminals into the same two sub graphs. The minimum cut problem consists of finding the cut, in a given graph, with the lowest cost.

4 SYSTEM TESTING

4.1 Test data collection

Since the project deals with image classification, many standard images are used for preprocessing, kernalizing and for clustering. The images from Berkley Dataset are used for classification.

4.2 Testing Parameters:

- Segmentation time
- Pixel label
- Pixel count

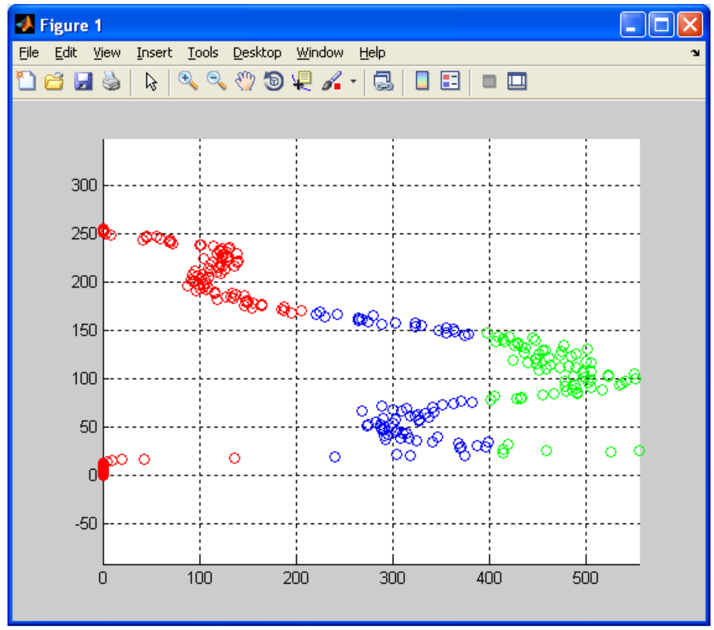

Fig:1 shows the results obtained on the basis of tree walk kernels. A maximum of 250 pixels can only be grouped

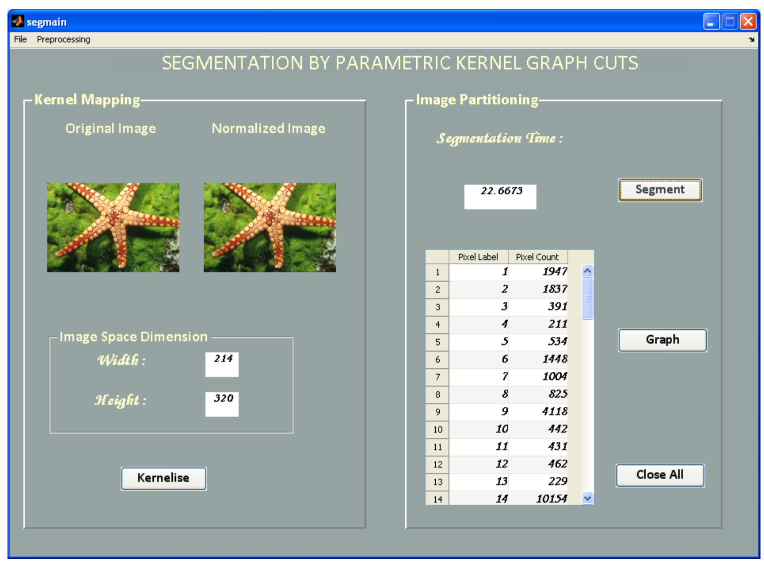

Fig 2:shows the pixel label and count along with the width and height of segmented image

5 Results

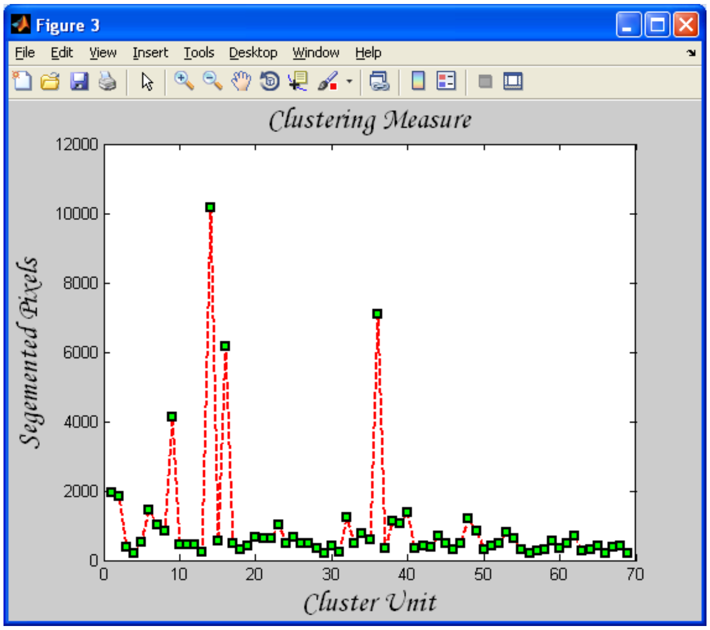

Fig 3:shows the results obtained through the proposed approach. It classifies around 10,000 pixels by a single label

5 FUTURE ENHANCEMENT

We can change the kernel function in such a way to improve the optimization process. Another new extension to this work would be to evaluate the improvement of using our segmentation algorithm as a first step in medical analysis such as tumor detection

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