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RESEARCH ARTICLE

INTERACTIVE IMAGE SEGMENTATION BASED ON HARMONIC FUNCTIONS & RECONSTRUCTIONS

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Abstract— This paper gives idea GRF functions instead of a graph-based algorithm for interactive image segmentation. Specifically, given a 3 X 3 local window, the colour of each pixel in it will be linearly reconstructed with those of the remaining eight pixels. The optimal weights will be transferred to linearly reconstruct its class label. This treatment is largely motivated from the manifold learning algorithm of locally linear embedding. But beyond LLE where only one data point is reconstructed in each given data neighbourhood, it will reconstruct all the pixels in each spatial window. In this process, the label reconstruction errors are estimated. The information about the user-specified foreground and background is introduced into a regularization framework. The segmentation task is finally solved via global optimization.

Key Terms: - interactive segmentation; GRF functions; LLE functions; graph based algorithm; manifold learning algorithm

I. INTRODUCTION

Image segmentation has often been defined as the problem of localizing regions of an image relative to content. Recent image segmentation approaches have provided interactive methods that implicitly define the segmentation problem relative to a particular task of content localization. The approach to image segmentation requires user guidance of the segmentation algorithm to define the desired content to be extracted. The past decades have yielded many approaches; automatically segmenting natural images is still a difficult task. The difficulties lie in two aspects. On the low level, it is difficult to model properly the visual elements. On the high level, it is difficult to group truthfully the visual patterns. In view of pattern classification, such a labelling is fundamentally important as it helps to reduce the complexity of pattern modelling as well as the ambiguity of pattern grouping. This paper gives idea about how interactive segmentation done through multiple linear reconstructions and using GRF functions. A practical interactive segmentation algorithm must provide four qualities: 1) Fast computation, 2) Fast editing, 3) An ability to produce an arbitrary segmentation with enough Interaction, 4) Intuitive segmentations.

In multiple lines reconstruction, the same user strokes can generate more accurate segmentations on most complex natural images where graph cut and random walks do. All independent of data and need not be tuned well from image to image. The core computation can be easily implemented. The most complex computation is to solve sparse symmetrical linear equations. In single linear reconstructions provides inaccurate image segmentation. Object's area information is incorporated by the regional level attention rules for salient object detection.

This paper presents GRF functions instead graph-based algorithm for interactive image segmentation. Specifically, given a 3X 3 local window, the color of each pixel in it will be linearly reconstructed with those of the remaining eight pixels. The optimal weights will be transferred to linearly reconstruct its class label. This treatment is largely motivated from the manifold learning algorithm of locally linear embedding.

In this let us discuss interactive image segmentation approaches and methods used for implementations. In this paper compare several techniques of interactive image segmentation.Section II reviews the relationship of this work to previous approaches. In Section III, the algorithm is presented and analyzed. Section IV reports the experimental results. The conclusions will be drawn in Section V.

II. PRIOR WORK

Image segmentation is a vast topic. Therefore, we limit our review to supervised and graph-based algorithms. Additional work on random walks and combinatorial harmonic functions will also be discussed.

A. Supervised segmentation

Supervised segmentation algorithms [7] typically operate under one of two paradigms for guidance: 1) Specification of pieces of the boundary of the desired object or a nearby complete boundary that evolves to the desired boundary, 2) Specification of a small set of pixels belonging to the desired object and a set of pixels belonging to the background.

B. Graph-based methods of image segmentation

The graph cuts segmentation algorithm has been extended in two different directions of speed, color images and the user interaction. The first type of extension to the graph cuts algorithm[5] has focused on speed increases by coarsening the graph before applying the graph cuts algorithm. This coarsening has been accomplished in two manners: by applying a standard multilevel approach and solving subsequent, smaller graph cuts problems in a fixed band to produce the final, full-resolution segmentation & by applying a watershed algorithm [6] to the image.

C. Random walks and combinatorial harmonic functions

Harmonic functions defined on graphs with given Dirichlet boundary [3] conditions have seen recent interest in many applications, including image filtering, image colorization and machine learning. Combinatorial harmonic functions were also famously employed by Tutte for graph drawing.[2]

D. Interactive Graph Cuts

The user marks certain pixels as object to provide hard constraints for segmentation. Additional constraints incorporate both boundary and region information. Cuts are used to find the globally optimal segmentation of the N-dimensional image. It provides a globally optimal solution for an N-dimensional segmentation [10] when the cost function is clearly defined. A globally optimal segmentation can be very efficiently recomputed when the user adds or removes any hard constraints .This allows the user to get any desired segmentation results quickly via very intuitive interactions. The segmentation boundary can be anywhere to separate the object seeds from the background seeds.

III. MOTIVATION

A. Problem Formulation

The problem of interactive image segmentation can be formulated as follows. Given an image I with n=h X w with pixels $p_{i=1}^{n}$.Two labeled pixel sets of foreground F, and background B, the task is to assign a label "foreground" or background" to each of the unlabeled pixel. Each pixel can be described with a feature vector with $X_{i=}[r, g,b]^T$ in, where is the normalized color of in RGB color space, namely 0< r,g,b<1.

B. Motivation

To develop a graph-based algorithm of transductive classification, the key is to properly represent the pixels in each window. To this end, we consider to linearly reconstruct their colors. This treatment is reasonable as in general the colors of the neighboring pixels are similar to each other.

Given pixel, Pi £ I and its 3 X 3 spatial neighborhood with p_i at the center, we further denote the color set of these pixels, $N_i=[X_{i,j}]_{j=1}^{9}$ where i_j £ [1,2, .,.,n] is a unique index in X_i. For pixel P_i, we use its eight neighbors surrounding it to linearly reconstruct its color vector X_i.

$$x_{i} = w_{i,2}x_{i2} + \ldots\ldots\ldots\ldots\ldots + w_{i,9}x_{i9}$$

Where $w_{i,j\ (j=2,3,..,\ 9)}$ are the reconstruction weights. The optimal weights can be obtained by minimizing the squared reconstruction error.

$$W_i = (x^T{}_{i,j}\, x_{i,j} + \lambda I)^{-1} 1 \,/\, I^T(X_{i,j}{}^T X_{i,j} + \lambda I)$$

Where $w_{i=}$ $[w_{i,2\ldots\ldots\ldots\ldots}\ w_{i,9}]^T$ £ $R^{8.}$ And I is a 8 X 8 identity matrix, and λ is a small positive parameter introduced to avoid the singularity of $X_i{}^T X_i$.

The optimal weights are estimated, they are transferred to linearly reconstruct the class label.

$$F_{i,j \approx \sum w\ i,j,s,fi.}$$

Squared reconstruction error:

$$e_{i,j} = (f_{i,j} - \textstyle\sum_{s \neq j} w_{i,j,s}\, f_i)^2$$

It is rewritten as:

$$e_{i,\,j} = f_i{}^T M_{i,j} f_i$$

Where,

$$M_{i,j} = w_{i,j} w_{i,j}{}^T \text{ £ } R^{9x9}$$

The class labels are unknown; an alternative way to evaluate the quality of the model is to calculate the squared reconstruction error, $\|x_i - x_i\|$. It is desired to obtain the minimum reconstruction error with its eight pixels surrounding it.

The minimum color reconstruction error of a pixel may be obtained not by the eight pixels surrounding it. To utilize the above information, for each pixel in a spatial window, we linearly reconstruct its color vector with those of the remaining pixels in it. The reconstruction weights will be kept to reconstruct their class labels. The label reconstruction errors will be minimized in way of global optimization.

C. Solving Class Labels for Interactive Image Segmentation for Multiple Reconstruction

Goal is to minimize evaluated on the grid graph, to achieve the goal of interactive image segmentation, it is also necessary to minimize the label prediction errors of the pixels specified by the user in the human-computer interface. By summing these errors together, an objective function can be constructed as follows:

$$G(f) = f^T M f +_{\gamma} (\textstyle\sum_{Pi\ £ f} (1-f_i)^2 + \sum_{pi £ B} (-1-f_i)^2)$$

Minimizing G (f) will output “+1” for each of the user specified foreground pixels, and for each of the user specified background pixels. Thus in this case, the class labels of the user labelled pixels will be exactly satisfied. In computation, we can take as a large positive number. By differentiating the objective function G (f) and setting the derivative to be zero.

$$(M +_{\gamma} C) f = y$$

Where C is the diagonal matrix

C (i,i) = {1,if pixel is labelled by user.
C(i,i) = { 0 ,otherwise.

D. Solving Class Labels for Interactive Image Segmentation for Random Walk

In random walk each seed specifies a location with a user-defined label. A random walker starting at this location, the probability that it first reaches each of the K seed points. Calculation may be performed exactly without the simulation of a random walk. By performing the calculation, we assign a K-tuple vector to each pixel that specifies the probability that a random walker starting from each unseeded pixel will first reach each of the K seed points. A final segmentation may be derived from these K-tuples by selecting for each pixel the most probable seed destination for a random walker.

E. Solving Class Labels for Interactive Image Segmentation for GRF Functions

The problem of finding a harmonic function subject to its boundary values is called the Dirichlet problem. The harmonic function[9] that satisfies the boundary conditions minimizes the Dirichlet integral, since the Laplace equation is the Euler-Lagrange equation.

The combinatorial Laplacian matrix

$$L_{i,j} = \begin{cases} d_i & \text{if } i=j \\ -w_{i,j} & \text{if } v_i \;\&\; v_j \text{ are adjacent nodes} \\ 0 & \text{otherwise} \end{cases}$$

Where $L_{i,j}$ is indexed by vertices v_i & v_j.

Define the m X n edge-node incidence matrix as

$$A_{e_{i,j} v_k} = \begin{cases} +1 & \text{if } i=k \\ -1 & \text{if } j=k \\ 0, & \text{otherwise} \end{cases}$$

For every vertex vk and edge eij , where each eij has been arbitrarily assigned an orientation. The Laplacian matrix above, Aeijvk is used to indicate that the incidence matrix is indexed by edge eij and node vk. to solve for the harmonic function that find potentials on unseeded nodes, while keeping the seed nodes fixed.

A combinatorial formulation of the Dirichlet integral.

$$D[x]= 1/2(Ax)^T C(Ax = 1/2 \; x^T Lx=1/2 \sum_{e_{i,j} £ E} (w_{i,j} (x_i - xj)^2)$$

Combinatorial harmonic is a function x .Since L is positive semi-definite, the only critical points of D[x] will be minimal.

F. Algorithm of MLRW

Input: Image with pixels to be segmented; the set of the user-specified foreground pixels and the set of the user- specified background pixels two parameters r and l

Output: The segmentation of F $\mathcal{L}$
1: Construct X where x=[r,g,b] .
2: Allocate a sparse matrix .
3: **for** each pixel , pi=1,2,3, ,n **do n**
4: Allocate a zero matrix .
5: **for j=1,2,3,……….9** , **do**
6: Calculate ,Mij.
7: .Mij=Mi+Mj
8: **end for**
9: M=M+SMiSj.
10: **end for**
11: Construct diagonal matrix .
12: Construct vector .
13: Solve ,f.
14: **for** ,i=1,2,……..n **do**
15: Label as "pi ", if ; " ", otherwise.
16: **end for**

The performance of reconstructing, respectively, all of the pixels in 3X 3 windows will not be equivalent to that of reconstructing only the center pixel in 5 X 5 windows. Reconstructing the center pixels even with large image windows may still generate unsatisfactory results. This in turn indicates that MLRW is not equivalent to SLRW with large windows.

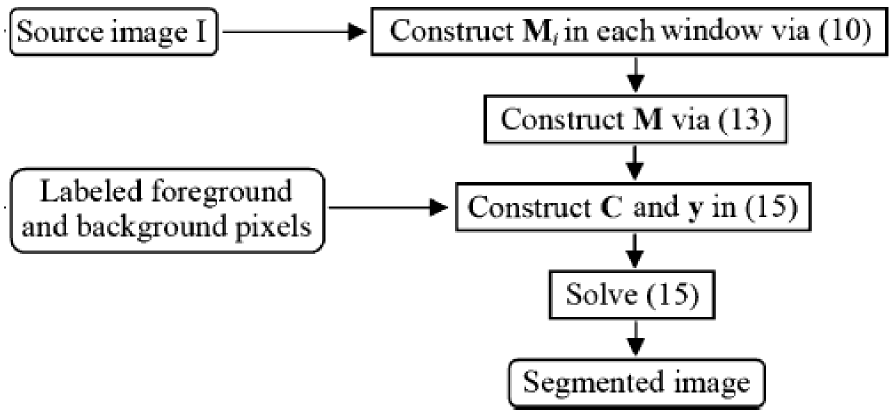

Fig .1.Flowchart of the algorithm

IV. EXPERIMENTAL RESULTS

A. Comparison

MLRW with the commonly-used algorithms of graph cut (GC) and RW in interactive image segmentation. We also compare it with the classical transductive algorithms of GRF and LLGC. In addition, SLRW will be also compared to illustrate the effectiveness of algorithm. In GC, the algorithm is implemented. The label likelihoods of pixels are calculated via the approach used. To speed up the calculation, Kmeans clustering algorithm[4] with 20 clusters is run to cluster, respectively, the colours of the user-specified foreground and background pixels.

GC can generate satisfactory segmentations where the foreground and background pixels have different colours. If the foreground and background have similar colours and those colours are not labelled by the user, GC may generate unsatisfactory segmentations. RW is a powerful algorithm. However, it may also generate unsatisfactory results for complex natural images. More user-specified strokes are needed to guarantee that the random walk starting from an unlabeled pixel meets first the labelled pixel belonging to its own class.

GRF generate unsatisfactory results. More user-specified strokes are needed to block the leaking of label propagation into the unwanted regions. In addition, the segmentations also indicate that MLRW significantly outperforms SLRW. The segmentation accuracy is calculated as the ratio of correct segmented pixels with respect to the ground truth segmented by gaussian stochastic process [8]. When the stochastic process concerns an entire region of space we talk about a Gaussian random field.

In a homogeneous Gaussian random field [1] the one-point Gaussian distribution the probability at any one location within that volume for having a value Yc = [y; y + dy] is given by the one-point Gaussian distribution. Image window with the same pixel colour, the Laplacian matrix deduced by LSR will equal to a unique constant Laplacian matrix. MLRW can speed up LSR.The Laplacian matrix in LSR will be replaced by a constant Laplacian matrix. MLRW can be solved iteratively by combining conjugate gradient, image pyramid, and multi-grid methods

B. Advantages

Both of them have their own explicit meanings, which are all independent of data .Need not be tuned well from image to image. The most complex computation is to solve sparse symmetrical linear equations. The main computation time will be taken to fulfill the linear reconstructions in the windows of 3 X 3 pixels.

V. CONCLUSION

The key idea is to linearly reconstruct the colour vector of each pixel with those of the remaining pixels also in the window. The estimated optimal reconstruction weights are transferred to linearly reconstruct the class label of each pixel. In this way, the label reconstruction errors are estimated and minimized to obtain the finally segmentation. . It is used in different areas of medical imaging MRI flooding & machine versions. In the existing top-down methods is that they significantly depend upon the accuracy of image segmentation, and the performance of these methods may be degraded by inaccurate image segmentation. In this all images are all independent of data .It need not be tuned well from image to image. The most complex computation is to solve sparse symmetrical linear equations. More time will be taken and large memory will be required to fulfil the segmentation.

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