SURVEY ON INTERACTIVE METHODS FOR IMAGE SEGMENTATION

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ABSTRACT

Segmentation partitions an image into distinct regions containing each pixels with similar attributes. To be meaningful and useful for image analysis and interpretation, the regions should strongly relate to depicted objects or features of interest. Meaningful segmentation is the first step from low-level image processing transforming a grayscale or color image into one or more other images to high-level image description in terms of features, objects, and scenes. Interactive segmentation became popular because in different domains, user interaction is available, and it can greatly reduce the ambiguity of segmentation caused by complex object appearance, weak edges, etc. Global optimization, often formulated as a graph problem, became popular because it is more robust compared to the local methods such as thresholding or region-growing. These methods overcome the problems in old traditionally used approaches as they not only consider local pixel-based features, but also look at global similarities within the image. This paper reviews various interactive image segmentation methods and their algorithms.

1. INTRODUCTION

Image segmentation in general purpose is a highly ambiguous problem. In many applications, such as medical imaging, user guidance is available to help reduce the ambiguities in segmentation. Sometimes, even with a small amount of user interaction, segmentation quality is largely improved. Thus interactive segmentation techniques are becoming increasingly popular over the last decade.

Interactive segmentation mitigates the problems inherent to fully automatic segmentation, which seems to never be perfect. The interactive segmentation methods provide an easy way of segmenting complex objects from the image.

2. GRAPH BASED METHODS

As the name graph based, these methods represents the image and its contents as a graph. Certain neighboring pixels are connected by undirected edges based on selected edges from a graph. The image is segmented by minimizing a cost associated with cutting the graph into sub-graphs.

2.1 GRAPH CUTS

These are used to find the globally optimal segmentation of the N-dimensional image. This approach was introduced by Boykov and Jolly [1].

It is an interactive segmentation technique that divides an image into two segments: "object" and "background". A user imposes certain hard constraints for segmentation by indicating certain pixels (seeds) that absolutely have to be part of the object and certain pixels that have to be part of the background. Intuitively, these hard constraints provide clues on what the user intends to segment. The rest of the image is segmented automatically by computing a global optimum among all segmentations satisfying the hard constraints[2]. The cost function is defined in terms of boundary and region properties of the segments. These properties can be viewed as soft constraints for segmentation. A globally optimal segmentation can be very efficiently recomputed when the user adds or removes any hard constraints (seeds). This allows the user to get any desired segmentation results quickly via very intuitive interactions [3].

3. MINIMAL/MAXIMAL SPANNING TREE (MST) PROBLEM

Tree is a graph G without cycle

Fig-1: Tree Graph

The minimal spanning tree (MST) problem is one of the oldest and most basic graph problems in theoretical computer science [4]. Given an edge weighted graph, this problem calls for finding a sub tree spanning all the vertices, whose total weight is minimal.

The Minimal Spanning Tree problem is:

Input: A weighted graph (G, w) is required

Output: Unique spanning tree T that minimizes

$$\Sigma \in \in T^{\omega(\varepsilon).}$$

When G is not connected we find the minimal spanning forest MSF: A set of trees, one in each of the connected component of G, each tree being a minimal spanning tree of the graph induced by the component.

4. GRAB CUT METHOD

This method is an interactive foreground extraction using iterated graph cuts. It is the extension of the graph-cut approach in three respects. First, it develops a more powerful iterative version of the optimization. Secondly, the power of the iterative algorithm is used to simplify substantially the user interaction needed for a given quality of result. Finally, a robust algorithm for "border matting" has been developed to estimate simultaneously the alpha-matte around an object boundary and the colors of foreground pixels. For moderately difficult examples the proposed method outperforms competitive tools. It is an innovative 2D image segmentation technique [5].

5. S-T MIN CUT [6]

Undirected graph (V, E) with nodes v $\in$ V and edges $v\,v'$ $\in$ E $\subseteq$ ( )

Every edge $v\,v'$ $\in$ E has a non-negative weight $wv\,v' \geq 0$

Cut (S, T) is a partition of V into S and T such that $V = S \cup T$ and $S \cap T = \varnothing$

Weight of cut (S, T) is
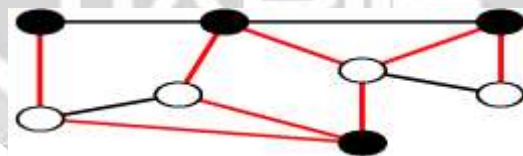
$$W(S, T) = \sum_{v \in S,\, v' \in T} wv\,v'$$

Fig-2: Graph for S-T min cut

Given two special nodes s and t, any cut (S, T) such that s $\in$ S, t $\in$ T is an s-t cut.

Image segmentation: Label each pixel either as background or as foreground

Formalize this task as follows:

Model the image as grid graph (V, E)

•Pixels are nodes v $\in$ V

•Pairs of neighboring pixels are edges $v\,v' \in$ E

Where xv = label of pixel v; x$v \in$ {F, B} (F is foreground, B is background)

fv = intensity/color of pixel v ; all intensities form vector f = (fv | v $\in$ V)

Compute the 'best' labeling x = (xv | $v \in$ V) from intensities f

For a good segmentation, a labeling x must satisfy two requirements:

1. Agreement with the input image intensities:

• Defined for each pixel independently

• p(B| fv) = probability that pixel with intensity fv belongs to background

• p(F | fv) = probability that pixel with intensity fv belongs to foreground

2. Contiguity of background and foreground:

• It is more likely that two neighboring pixels belong both to background or both to Foreground that one to background and one to foreground

• Probability defined for each pixel pair independently

$$p(x\chi_v,\chi_{v'}) = \begin{cases} a & \text{if } \chi_v = \chi_{v'} \\ b & \text{if } \chi_v \neq \chi_{v'} \\ & \text{Where } a > b \end{cases}$$

Best labeling x must maximize

$$\prod_{v \in V} p(\chi_v | fv) \quad \prod_{v\,v' \in E} p(\chi_v, \chi_{v'})$$

Minimize $F(X | f) = \sum_{v \in V} g(\chi_v | fv) + \sum_{v\,v' \in E} g(\chi_v, \chi_{v'})$

Taking negative logarithm:
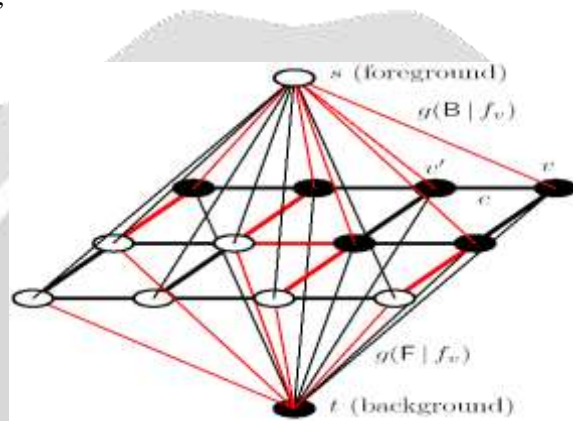
F(X | f)   = 'image energy'

Fig-3: s-t min cut

6. LAZY SNAPPING [7]

Here the composing a foreground object with an alternative background. In this, it removes a foreground object from a background, may be with automatic means then it will Creating a matte for further image enhancements (selective blurring, lighting conditions,)

• First step: foreground/background selection
– Only few strokes are needed
– Min-cut on segment level
• Second step: Boundary correction
– Min-cut on pixel level
Object Marking Step
• Easily segment foreground and background
• Mark seeds in each area
The Graph Cut algorithm solves the labeling problem, on a pixel level

7. MATTING

In Image processing, matting refers to the problem of estimating opacity (alpha value) and foreground and background colors for each pixel in the image. Specifically, the observed image I(z) (z = (x, y)) is modeled as a linear combination of foreground image F(z) and background image B(z) by an alpha map[8]:

I (z) = α_zF(z) + (1 − α_z)B(z) (1)

7.1 BAYESIAN VIDEO MATTING
An input image is a sequence of composite images with RGB pixels C(x, y, t). We assume that we can obtain an estimate of the background, which we label B(x, y, t). The unknowns then are the sequence of alpha mattes α (x,

y, t) and foreground colors F(x, y, t). Collecting the pixel location into a vector x = (x, y, t), and coloring unknowns red, we obtain the per-pixel compositing equations

$C_r(X) = \alpha_x F_r(X) + (1 - \alpha_x) B_r(X)$ $C_g(X) = \alpha_x F_g(X) + (1 - \alpha_x) B_g(X)$ $C_b(X) = \alpha_x F_b(X) + (1 - \alpha_x) B_b(X)$

The Bayesian formulation of the video matting problem now becomes one of finding the MAP estimate of the foreground image F and the alpha-matte α given C and B:

$$\{F, \alpha\} = \underset{F,\alpha}{\operatorname{argmax}}\ p(F, \alpha \mid C,B)$$

Using Bayes rule, posterior can be expressed as a combination of priors on F, α, C and B, and a conditional probability on C and B:

$$p(F, \alpha \mid C,B) = \frac{p(C,B \mid F, \alpha)\ p(F)p(\alpha)}{p(C)p(B)}$$

The MAP estimation is converted into an energy minimization by taking the negative log of the posterior, and noting that p(C) and p(B) do not depend on the unknowns F and α.

$$\{F,\alpha\}= \underset{F,\alpha}{\operatorname{argmax}}\{L(C, B \mid F,\alpha) + L(F) + L(\alpha)$$

Where L(C, B|F, and α.) is the reconstruction error (F) is the foreground energy and L (α.) is the negative log alpha prior [14].

7.2 HIGH RESOLUTION MATTING   VIA INTERACTIVE TRIMAP

Natural image matting addresses the problem of extracting an object from its background by recovering the opacity and foreground color of each pixel. Formally, the observed color C is a combination of foreground (F) and background (B) colors:

C = αF + (1- α.)B interpolated by opacity value α. (This simplified model will be reconsidered later). Matting is a highly under constrained problem and hence user interaction is essential. It can be classified into three types of user interfaces. The first class of interface is based on trimaps First the user paints a trimap by hand as accurately as possible, i.e. each pixel is assigned to one of three classes: foreground (F), background (B) or unknown (U). In a perfectly tight trimap the α values in U are above 0 and below 1 and F and B regions have only α values which are exactly 0 and 1 respectively. The information from the known regions (F, B) is used to predict for each unknown pixel the values for F, B and α. It is seen and we will confirm it, that if the trimap is perfect, the resulting matte is of very high quality. Simple approach to obtain a soft matte from a hard segmentation is to run existing trimap-based matting techniques in a band of constant width around the hard segmentation [9].

7.3 RANDOM WALKS FOR INTERACTIVE ALPHA-MATTING

The random walks is highly efficient and having following advantages: First, by leveraging a recent technique from manifold learning theory, we effectively use RGB values to set boundaries for the random walker, even in fuzzy or low-contrast images. Second, the algorithm is straightforward to implement, requires specification of only a single free parameter (set the same for all images), and performs the segmentation and alpha-matting in a single step. Third, the user may locally fine tune the results by interactively manipulating the foreground/ background maps. Finally, the algorithm has an inherit parallelism that leads to a particularly efficient implementation via the graphics processing unit (GPU) [10].

7.4 POISSON MATTING

Poisson matting is used to formulates the problem of natural image matting as one of solving Poisson equations with the matte gradient field. This technique has the following advantages. First, the matte is directly reconstructed from a continuous matte gradient field by solving Poisson equations using boundary information from a user-supplied trimap. Second, by interactively manipulating the matte gradient field using a number of filtering tools, user can further improve Poisson matting results locally until he or she satisfied. The modified local result is seamlessly integrated into final result [11].

Poisson matting is done in two steps. First, an approximate gradient field of matte is computed from the input image. Second, the matte is obtained from its gradient field by solving Poisson equations. In order to get an approximate gradient field of matte, we take the partial derivatives on both sides of the matting equation:

$\nabla I = (F - B)\, \nabla\alpha + \alpha\nabla F + (1 - \alpha)\nabla B$

Where $\nabla = (\partial/\partial x,\ \partial/\partial y)$ is a gradient operator. This is the differential form of the matting equation, for R, G and B channels individually. In situations in which foreground *F* and background *B* are smooth,

i.e., $\alpha\nabla F + (1 - \alpha)\nabla B$ is relatively small with respect to (F – B) we can get an approximate matte gradient field as follows:

$$\nabla\alpha \approx (1/ F – B) \nabla I$$

It means that the matte gradient is proportional to the image gradient.

7.5 BLUE SCREEN MATTING

It was used for live action matting and was the first technique. The principle is to photograph the subject against a constant-colored background, and extract foreground and alpha treating each frame in isolation. This single image approach is under constrained since, at each pixel, we have three observations and four unknowns. Vlahos pioneered the notion of adding simple constraints to make the problem tractable; this work is nicely summarized by Smith and Blinn [11]. For example, under the assumption that $.5 \leq a_2 \leq Fb \leq a_2F_g$, Vlahos constrained the set of equations with:

$$\alpha = 1- a_1 (C_b - a_2 C_g)$$

where C_b and C_g are the blue and green channels of the input image, respectively, and a1 and a2 are user-controlled tuning parameters. Additional constraint equations such as this one, however, while easy to implement, are *ad hoc*, require an expert to tune them, and can fail on fairly simple foregrounds [12].

8. SNAKE: ACTIVE CONTOUR MODELS

It is an energy minimizing spline guided by external constraint forces and influenced by image forces that pull it toward features such as lines and edges. Snakes are active contour models: they lock onto nearby edges, localizing them accurately. Scale-space continuation can be used to enlarge the capture region surrounding a feature [13]. Snakes provide a unified account of a number of visual problems including detection of edges, lines and subjective contours motion tracking and stereo matching[16].

9. LIVE WIRE

It formulates boundary detection as an optimal path search in a weighted graph. Optimal graph searching provides mathematically piece-wise optimal boundaries while greatly reducing sensitivity to local noise or other intervening structures. Robustness is further enhanced with *on-the-fly training* which causes the boundary to adhere to the specific type of edge currently being followed, rather than simply the strongest edge in the neighborhood[14]. Boundary cooling automatically freezes unchanging segments and automates input of additional seed points. Cooling also allows the user to be much more free with the gesture path, thereby increasing the efficiency and finesse with which boundaries can be extracted.

10.   INTELEGENT SECISORS

The anothe interactive tool called *Intelligent Scissors* which can be use for image segmentation. Fully automated segmentation is an unsolved problem, while manual tracing is inaccurate and laboriously unacceptable. However, Intelligent Scissors allow objects within digital images to be extracted quickly and accurately using simple gesture motions with a mouse. When
the gestured mouse position comes in proximity to an object edge, a *live-wire boundary* "snaps" to, and wraps around the object of interest.
It formulates boundary finding as an unconstrained graph search [15] in which the boundary is represented as an optimal path within the graph. The live-wire tool allows the user to interactively select an optimal boundary segment by immediately displaying the minimum cost path from the current cursor position to a previously specified "seed" point in the image. Some boundary based segmentation techniques compute a single optimal boundary based on some initial template or contour[17]. Rather than decide on a single optimal boundary, our livewire technique computes, at interactive speed, an optimal path from a selected seed point to every Other point in the image and lets the user choose, interactively, based on the current cursor position, the path which visually corresponds best to a segment of the desired object boundary[18].

11.   CONCLUSION

From the above discussion it is seen that there exist variety of segmentation methods. But no one is suitable for all types of input images. It is seen that the interactive methods gives the best possible results for the given data base. As per the requirement we choose any one that gives accurate segmentation. Thus there is a wide scope for research in Image segmentation.

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