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An Experiment with OneCut and Active Contour Segmentation Techniques

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Abstract: This paper puts forth our observations from the experiments conducted on relatively newer interactive segmentation technique – One Cut based on Graph Cut and Active Contour segmentation technique based on Level Sets, using Matlab software on selected natural images. The images were selected such that those have complexities and pose segmentation challenge. The objective of this experiment is to understand and assess the effectiveness of these techniques on select natural images, which have complex image composition in terms of intensity, colour mix, indistinct object boundary, low contrast, etc. We have used Jaccard Index, Dice Coefficient and Hausdorrf Distance as measures to assess the accuracy, besides visual assessment. The segmented images were compared with ground truth and then subjected to these accuracy measures. We have found OneCut to be much more effective than Active Contour.
Keywords: One Cut, Grab Cut, Active Contour, Level Sets, Interactive Segmentation.

I. INTRODUCTION

Extracting foreground object from background has been a challenge ever since the need came into existence. While the needs have been different for different purposes, so were the algorithm or techniques – each suitable to solve a specific problem or need. While hundreds of algorithms have been developed since last five decades, it seems we still do not have an algorithm which can be applied to all the images to successfully segment them. Newer algorithms and techniques are being developed at faster pace, but looks like it is still evolving.

Extracting areas of interest or foreground is the primary purpose behind image segmentation. Accuracy of the segmentation decides if the image can be directly fed into next application or further enhancement or processing is required on the segmented image.

Problems such as visual tracking, image segmentation, volume segmentation, etc., Active Contour methods have been quite effective and become popular. The basic idea is to allow a contour to deform so as to minimize a given energy functional in order to produce the desired segmentation. There are two main categories of active contours, viz. edge-based and region-based. As explained in [1, 2], Identification of object boundaries utilizing image gradients is quite well performed by Edge-Based active contour models. However, these methods are sensitive to noise and initial curve placement plays a crucial role in deciding segmentation outcome. In some situations, such a highly localized image information may be sufficient to yield decent segmentation outcome. One of the main benefit of these methods, is that global constraints are not required to be imposed on the image, as a result, in most of the complex images where foreground and background is complex or heterogeneous, correct segmentation can still be achieved.

There has been great work in active contours focused on region-based approach inspired by the region-competition work of Zhu and Yuille [3]. These approaches employ statistical methods to model the foreground and background and find an energy optimum where the model best fits the image. As elaborated in [4, 5, 6, 7], some of the most widely used and quite well known region based active contour models have a fundamental assumption that image regions are composed of constant intensity. Some more advanced approaches [8, 9, 10, 11] attempt combination of known distributions, texture maps, intensity histogram or structure tensors to model the regions. Region based approaches have advantages over edge based methods such as robustness against initial curve placement and insensitivity to image noise.

However, techniques that attempt to model regions using global statistics are usually not ideal for segmenting heterogeneous objects. In cases where the foreground cannot be easily distinguished from the background in terms of global statistics, region-based active contours may have erroneous outcome. Level Sets are great techniques and this paper discusses the experiments conducted using Active Contour. As explained in [12], the approach is, considering the problem to be statistical, 3D reconstruction is achieved and incremental process of deformation is applied to solve the optimization problem. This technique is based on previous works in 3D reconstruction and level set modelling and puts forth surface estimation from range data. To achieve the same, analytical characterization of the surface is performed such that it maximizes posterior probability. Also, [12] suggests a newer computational algorithm for level set modelling. This algorithm, called as sparse field algorithm, and has inherent advantages of level set modelling combined with the computational efficiency of parametric representation. This algorithm, as suggested by the authors is claimed to be more efficient than others, since, level set is assigned to specific grid points and level set model is positioned more accurately than the grid itself.

The active Contour technique is also called snakes; its implementation in Matlab is based on Sparse-Field level-set method, similar to the method described in [12] and evolves the segmentation using iterative process. This implementation in Matlab, uses either Chan-Vese [13] or Edge [14] based energy models.

In OneCut [15] technique which is relatively newer the authors have grouped segmentation algorithms into two major categories – techniques wherein known appearance models are assumed and the other, techniques which estimate appearance models jointly with segmentation. Appearance models are quite critical for many image segmentation algorithms. The authors observe that for fixed foreground and background appearance models, the most basic object segmentation energy [16, 17] usually combines boundary regularization with log-likelihood ratios. One important advantage of this basic energy is that there exist efficient methods for global minimization of this basic energy using graph cuts [18] or continuous relaxations [19, 20]. In many applications it is possible that the appearance models may not be known a *priori*. Model parameters as extra optimization variables are considered by well-known approaches to segmentation by [3, 4, 21] in their respective segmentation energies; and is known to be NP-hard [22]. In the interactive image segmentation technique GrabCut [21], initial appearance models are computed from a given bounding box.

For graph-cut based image segmentation the authors in [15] have proposed an appearance overlap term based on L1 distance between un-normalized histograms of foreground and background. The authors have also demonstrated that this proposed term is more effective at separating colours that compared to other separators and is quite easy to implement. The authors have claimed their OneCut algorithm finds global minimum in one cut as against other methods like GrabCut [21]. Also, the proposed technique claims to replace approximate iterative optimization techniques based on block coordinate descent [21].

II. ACCURACY MEASURES

In this experiment and similar to [23] segmented images were compared with ground truth to assess the accuracy of both the segmentation techniques. Segmented images were compared with the ground truth images to assess accuracy by computing Jaccard Index, Dice Coefficient & Hausdorrf Distance.

A. Jaccard Index

The Jaccard Index [24], also known as the Jaccard similarity coefficient, is a statistic used for comparing the similarity and diversity between the two sets. The Jaccard coefficient measures similarity between finite sample sets, and is defined as the size of the intersection divided by the size of the union of the sample sets:

$$J(A,B) = \frac{|A \cap B|}{|A \cup B|} = \frac{|A \cap B|}{|A| + |B| - |A \cap B|}$$

Eq. (1)

The Jaccard distance is obtained by subtracting the Jaccard coefficient from 1 and indicates dissimilarity between two sets. It is complementary to the Jaccard coefficient and is expressed by dividing the difference of the sizes of the union and the intersection of two sets by the size of the union:

$$d_J(A,B) = 1 - J(A,B) = \frac{|A \cup B| - |A \cap B|}{|A \cup B|}$$

Eq. (2)

B. Dice Coefficient

The Sørensen–Dice index [25], which is independently developed by the botanists Thorvald Sørensen and Lee Raymond Dice, is also an indicator used for comparing the similarity of two sets. Sorensen's formula was intended to be applied to presence/absence data, and is –

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$$QS = \frac{2 \mid A \cap B \mid}{\mid A \mid + \mid B \mid}$$

Eq. (3)

Where, |*A*| and |B| are the numbers of species in the two samples. QS is the quotient of similarity and ranges between 0 and 1. It can be viewed as a similarity measure over sets.

C. Hausdorrf Distance

The Hausdorrf distance [26], is also known as Hausdorrf metric, and it measures how far two subsets of a metric space are from each other. Hausdorrf distance is the greatest of all the distances from a point in one set to the closest point in the other set. Let X and Y be two non-empty subsets of a metric space (M, d). We define their Hausdorrf distance $d_H(X, Y)$ as –

$$d_H(X,Y) = \inf \{\epsilon \geq 0;\ X \subseteq Y_\epsilon \text{ and } Y \subseteq X_\epsilon\}$$

Eq. (4)

Where,

$$X_\epsilon \bigcup_{x \in X} \{z \in M ;\ d(z,x) \leq \epsilon$$

Eq. (5)

III. THE EXPERIMENT

In this experiment, we have studied OneCut [15] and Active Contour based on Sparse Field Level Sets [12] techniques and performed experiments using MATLAB software, to understand and study effectiveness of these techniques and accuracy of segmentation by assessing –

1) Visual confirmation
2) Jaccard Index
3) Dice Index
4) Hausdorrf Distance

The experiment involved performing segmentation, using varying parametric values, study the impact on the output and such combination was chosen which had resulted in best output for final segmented image. For this experiment, select images from Single Object Image Segmentation Dataset of natural images [27] has been used. This dataset is made freely available for research purposes, by Department of Computer Science and Applied Mathematics, Weizmann Institute of Science. This image dataset provides source image as well as ground truth for comparison. As stated in [27], Ground Truth has been constructed using manual segmentation by human subjects. We have used RGB images as an input to the segmentation process. The ground truth images were converted into binary using GIMP toolkit [28]. Following process was followed in this experimental study.

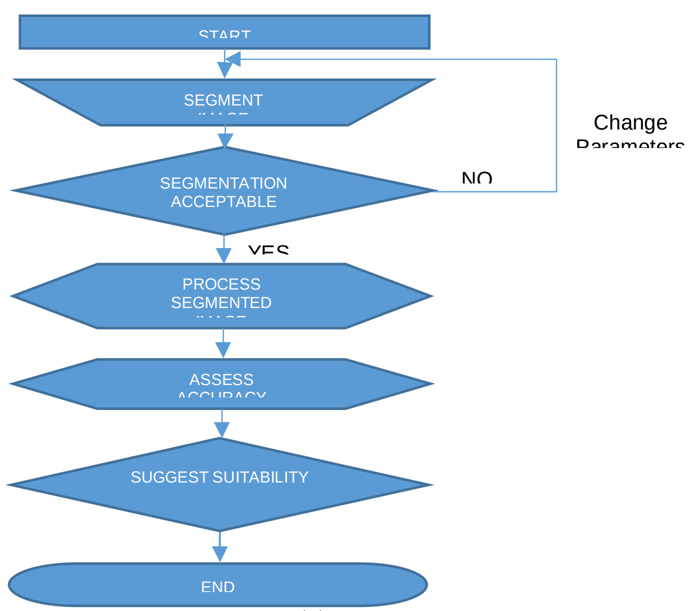
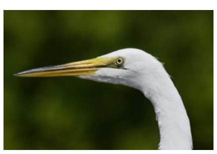


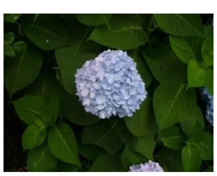
Figure (1)

IV. OBSERVATIONS

The experiment was conducted on various images, however, we have referred only 10 images which we considered to be complex to pose a segmentation challenge to the techniques with the intent to assess its suitability. All the images were RGB images. The images have been resized to fit this document. The Active Contour experiment was conducted using Matlab version 2017a, however, the OneCut technique was implemented in C language, on Windows PC. It was observed that Active Contour is computationally expensive and more the iterations, longer it took for the segmentation to occur. For Active Contour, iterations and smoothness factor did impact the output of the segmentation and only best output is chosen for comparison with OneCut. One-Cut was quite faster as compared to Active Contour.

Segmentation Set I			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.9493	0.9651
Dice Coefficient		0.9740	0.9823
Hausdorrf Distance		4.000	3.3166

Segmentation Set II			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.9355	0.9854
Dice Coefficient		0.9667	0.9926
Hausdorrf Distance		6.1644	5.3852

Segmentation Set III			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.9723	0.9686
Dice Coefficient		0.9860	0.9841
Hausdorrf Distance		3.1623	3.0000

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Segmentation Set IV			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.7610	0.9556
Dice Coefficient		0.8643	0.9773
Hausdorrf Distance		4.7958	3.1623

Segmentation Set V			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.7463	0.9738
Dice Coefficient		0.8547	0.9867
Hausdorrf Distance		9.4340	5.0990

Segmentation Set VI			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.8774	0.9556
Dice Coefficient		0.9347	0.9773
Hausdorrf Distance		6.1644	3.1623

Segmentation Set VII			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.8563	0.9797
Dice Coefficient		0.9226	0.9897
Hausdorrf Distance		4.6904	2.0000

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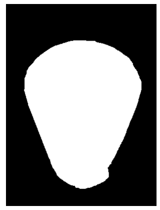
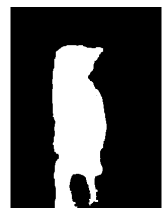
Segmentation Set VIII			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.8880	0.9748
Dice Coefficient		0.9407	0.9872
Hausdorrf Distance		6.4807	3.0000

Segmentation Set IX			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.8842	0.8842
Dice Coefficient		0.9385	0.9385
Hausdorrf Distance		4.8990	4.8990

Segmentation Set IX			
Original Image	Ground Truth	Segmented Image (Active Contour)	Segmented Image (OneCut)
			
Jaccard Index		0.8672	0.8672
Dice Coefficient		0.9289	0.9289
Hausdorrf Distance		5.9161	5.9161

As is evident from the above Segmentation Sets, by visual confirmation, OneCut has been largely successful on all the images, however, Active Contour has failed on most of them, barring first three. The Segmentation Set I, II and III have striking difference between the foreground and background colours and Active Contour was able to delineate the foreground quite well with as less as 100 iterations. However, in the subsequent Segmentation Sets IV to X, the object boundary has similarity in parts with background and Active Contour has failed to segment correctly even at 5000 iterations.

One Cut, with the ability to mark foreground and background pixels during the segmentation process, has great impact on the output. Although OneCut has succeeded on the Segmentation Sets IV to X, too many seeds were required both for foreground and background marking and some of the objects in the sets needed manual tracing of the object boundary to get successful segmentation output. Without this manual tracking, the segmentation had unacceptable output, similar to Active Contour.

In the Segmentation Set IV, the high intensity line running along the edge has impacted the segmentation output. Active Contour could not distinguish the edge correctly as it got mixed up with background texture and has resulted in failed segmentation. On the other hand, OneCut has very successfully separated the colours and has yielded successful segmentation.

In the Segmentation Set V to X, there exists similarity in the background and the foreground at quite a few places and Active Contour has again failed to delineate the foreground correctly. This similarity has interfered with the Active Contour segmentation process and has resulted in loss of information for all such areas in the segmented images, to an extent that it is quite unacceptable. OneCut, however has been quite successful, however, much more seeds were required to mark foreground and background areas to achieve desired output. However, minimum scribble width being wider than the thickness of the foreground object, has resulted in loss of information in the Segmentation Set X, alternatively, if this fine thread belonging to foreground is marked with scribble, additional adjoining areas also get included in segmentation output.

V. DISCUSSION

Both the techniques fall under category of interactive segmentation techniques, Active Contour is based on Level Sets and the algorithm used in this experiment is similar to the one described in [12]. Level Set Methods are excellent tool for numerical analysis of surfaces and shapes. When compared with parametric models, Level set models suffer from various drawbacks [12], e.g. large computational needs, absence of direct efficient representation of surface during deformation, finite resolution imposed by discrete approximation to the scalar field, etc.

There are other implicit Level Set representations [29], which are an alternative to parametric models, which specify model as level set of scalar function sampled on a discrete rectilinear grid. And has advantages especially in the context of deformation and reconstruction. These are topologically flexible and can split into pieces [12, 30, 31]. Variational approach employing deformable models can yield goal driven deformations [32, 33, 34]. Amongst these Level Set Methods, the Sparse Field method introduced in [12] is much faster as compared to other Level Set Methods. However, there are areas for improvement, such as problem of large data sets, prior, distortion due to second order smoothening, etc.

OneCut technique as described in [15] proposes appearance overlap penalty, and can be seen as special case of high-order label consistency term suggested by [36, 37] and a simpler construction specific constraint. Unlike NP-hard, multi-label problems discussed in [36, 37], the focus is on binary segmentation where such high-order constraints can be globally minimized. As against earlier methods [21, 22, 38, 39], the proposed method in [15] seems to get similar or better results at faster run times and demonstrates fast globally optimal binary segmentation technique explicitly minimizing overlap between foreground & background colour distributions.

Findings of this experiment also suggest successful segmentation on all the images achieved using OneCut technique. There has been further work done by [40], wherein energy-based formulation for convexity prior in discrete optimization framework has been proposed to further improve the quality of the segmentation process. Also, in [41], the authors have claimed that the proposed algorithm improves the output in many applications including appearance entropy minimization in [15]. And inspired by [15], very recently, the authors in [42] have built undirect graph with auxiliary nodes to find an optimal functional which minimizes the energy. Unlike [15, 42], there have been newer methods like SuperCut [43] which neither seem to employ auxiliary node nor iterative steps and claims to have much better output based on superpixels.

VI. CONCLUSION

The output of Active contour on these complex images would require post processing before further subjecting to applications. Since Active Contour employs iterative process, it has tendency to consume more time and system resources, while OneCut, was found to be very fast as it requires just one pass through the image. OneCut was found to be largely successful on all the images, although more seeds were required for marking foreground and background, but the output is much cleaner, complete and acceptable in most situations for further application use. Finer foreground objects which are thinner than the scribble width, may pose a challenge for OneCut in segmenting correctly. Active Contour could only segment images which have very distinct foreground from background, however, OneCut could segment all the images quite successfully. Contrary to Active Contour, output of OneCut can be fed directly to next applications.

VII. ACKNOWLEDGMENT

We acknowledge the great work done by the authors of Active Contour and OneCut interactive image segmentation techniques. Both these techniques are quite popular and useful for fellow researchers to study various aspects of image segmentation.

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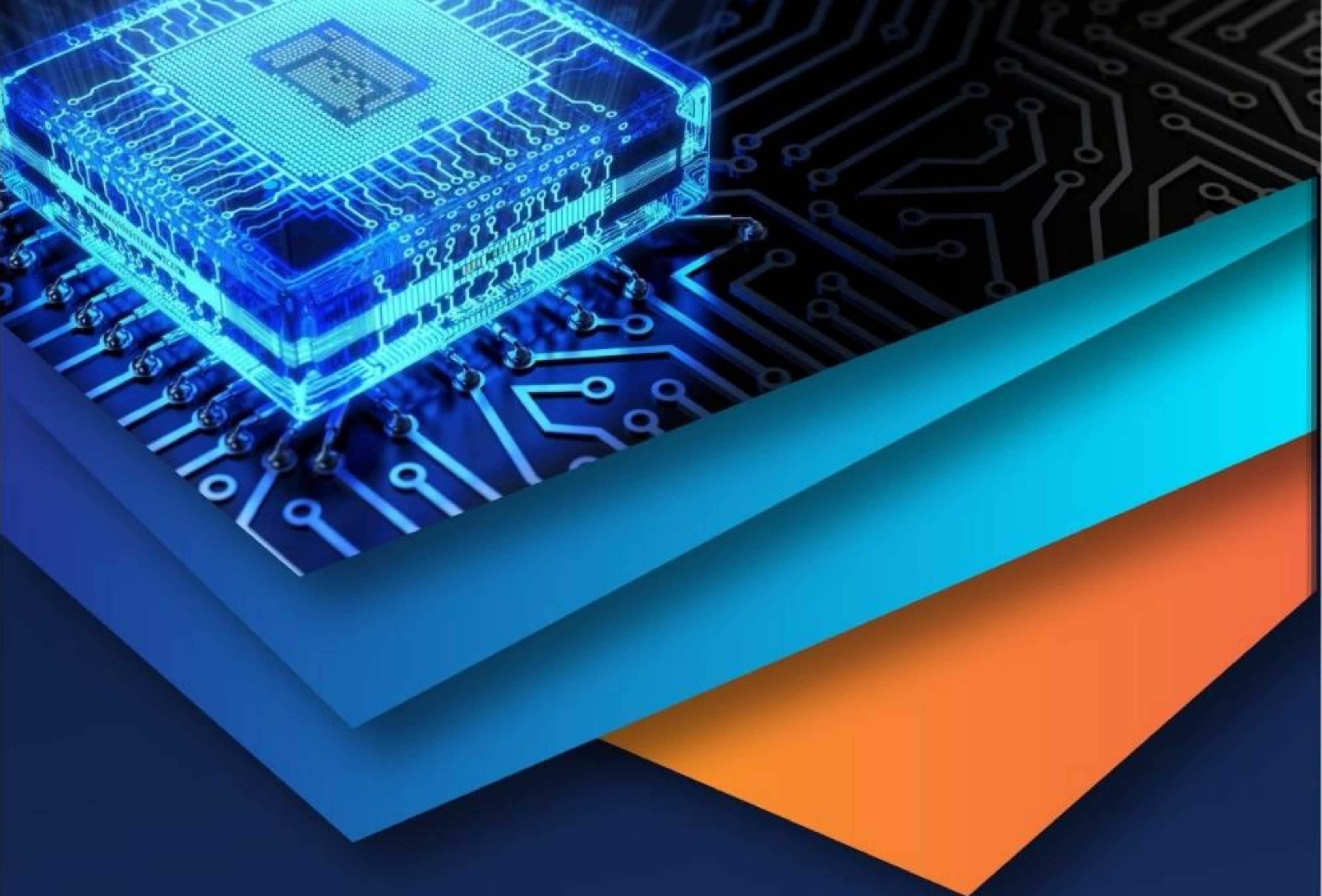

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