An Experiment with Sparse Field and Localized Region Based Active Contour Interactive Segmentation Techniques on Specific Images

Anuja Deshpande *anuja_1978@yahoo.com*
Department of Electronics,
Kamla Nehru Mahavidyalaya, Sakkardara,
Nagpur, Maharashtra, India 440024

Pradeep Dahikar *pbdahikarns@rediffmail.com*
Department of Electronics,
Kamla Nehru Mahavidyalaya, Sakkardara,
Nagpur, Maharashtra, India 440024

Pankaj Agrawal *pankaj_rknec@rediffmail.com*
Department of Electronics and Communication Engg.,
G. H. Raisoni Academy of Engineering and Technology,
Nagpur. Maharashtra, India 440028

Abstract

This paper discusses various experiments conducted on different types of Level Sets interactive segmentation techniques using Matlab software, on select images. The objective is to assess the effectiveness on specific natural images, which have complex image composition in terms of intensity, colour mix, indistinct object boundary, low contrast, etc. Besides visual assessment, measures such as Jaccard Index, Dice Coefficient and Hausdorrf Distance have been computed to assess the accuracy of these techniques, between segmented and ground truth images. This paper particularly discusses Sparse Field Matrix and Localized Region Based Active Contours, both based on Level Sets. These techniques were not found to be effective where object boundary is not very distinct and/or has low contrast with background. Also, the techniques were ineffective on such images where foreground object stretches up to the image boundary.

Keywords: Sparse Field Matrix, Localized Region Based Active Contours, Level Sets, Suitability, Interactive Image Segmentation, Effectiveness.

1. 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.

Active contour methods have become very popular and have found its use in wide range of problems solving including visual tracking and image segmentation. As elaborated in [1], 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 [2, 3], Edge-based active contour models utilize image gradients in order to identify object Boundaries. This type of highly localized image information is adequate in some situations, but has been found to be very sensitive to image noise and highly dependent on initial curve placement. One benefit of this type of approach is the fact that no global constraints are placed on the image. Thus, even if the foreground and background is complex and/or heterogeneous correct segmentation can still be achieved in certain cases.

There has been great work in active contours focused on region-based approach inspired by the region-competition work of Zhu and Yuille [4]. These approaches model the foreground and background regions statistically and find an energy optimum where the model best fits the image. Some of the most well-known and widely used region-based active contour models assume the various image regions to be of constant intensity [5, 6, 7, 8]. More advanced techniques attempt to model regions by known distributions, intensity histograms, texture maps, or structure tensors [9, 10, 11, 12]. As expressed in [1], there are many advantages of region-based approaches when compared to edge-based methods including 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 object to be segmented cannot be easily distinguished in terms of global statistics, region-based active contours may lead to erroneous segmentations.

Level Sets are great techniques and this paper discusses the experiments conducted using two of its variants, namely Sparse Field Matrix and Localized Region Based Active Contours. As explained in [13], the strategy is to formulate 3D reconstruction as a statistical problem and optimization problem is solved by an incremental process of deformation. This technique is built on previous works in both, 3D reconstruction and level set modelling and presents a fundamental result in surface estimation from range data using an analytical characterization of the surface that maximizes posterior probability. Also it presents a novel computational technique for level set modelling, called the sparse field algorithm which combines advantages of level-set approach with the computational efficiency of parametric representation. Sparse Field algorithm uses level sets of volumes as a means of representing and manipulating object shapes. The sparse-field algorithm claims to be more efficient than other approaches since, it assigns level set to specific set of grid points and positions the level-set model more accurately than the grid itself.

As elaborated in [1], the authors have proposed a new method, which allows any region based energy to be reformulated in local way and evolves contour based on local information. Localized contours are capable of segmenting objects with heterogeneous feature profiles that would be difficult to capture correctly using a standard global method. The authors claim that the presented technique is versatile enough to be used with any global region-based active contour energy and instill in it the benefits of localization.

2. ACCURACY MEASURES

Similar to and as expressed in [14, 15], in this experiment also we have assessed the accuracy of the segmentation by computing Jaccard Index, Dice Coefficient & Hausdorrf Distance on segmented images by comparing with ground truth.

2.1 Jaccard Index

The Jaccard Index [16], also known as the Jaccard similarity coefficient by Paul Jaccard, is a statistic measure used for comparing the similarity and diversity of sample 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:

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

EQUATION 1: Jaccard Index.

The Jaccard distance, which measures dissimilarity between sample sets, is complementary to the Jaccard coefficient and is obtained by subtracting the Jaccard coefficient from 1, or, equivalently, by dividing the difference of the sizes of the union and the intersection of two sets by the size of the union:

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

EQUATION 2: Jaccard Distance.

2.2 Dice Coefficient

The Sørensen–Dice index [17], also known by other names, is a statistic used for comparing the similarity of two samples. It was independently developed by the botanists Thorvald Sørensen and Lee Raymond Dice. Sorensen's original formula was intended to be applied to presence/absence data, and is

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

EQUATION 3: Dice Coefficient.

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.

2.3 Hausdorrf Distance

The Hausdorrf distance [18], named after Felix Hausdorrf is also known as Hausdorrf metric, 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

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

Where,

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

EQUATION 4: Hausdorrf Distance

3. THE EXPERIMENT

In this experiment, we have studied Level Set techniques viz. Localizing Region-Based Active Contours as described in [1] and Sparse Field Matrix as described in [5, 13] and performed experiments using MATLAB, to understand and study effectiveness of these techniques and accuracy of segmentation by assessing –

a) Visual confirmation
b) Jaccard Index
c) Dice Index
d) Hausdorrf Distance

The experiment involved performing segmentation, using varying values to study the impact on the output and such combination was chosen which resulted in best output for final segmented image. For this experiment, select images from Single Object Image Segmentation Dataset of natural images [19] 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 [19], Ground Truth has been constructed using manual segmentation by human subjects. We have used colour images as an input to the segmentation technique, whose output is also a colour (RGB) image, with extracted foreground and black background.

Ground Truth images were also converted to binary images so that a comparison can be done with segmented images. The source images, segmented images and findings are listed below. Following images have been resized using Microsoft Word to fit this document.

Following steps were performed in this experiment, similar to done in [14, 15].

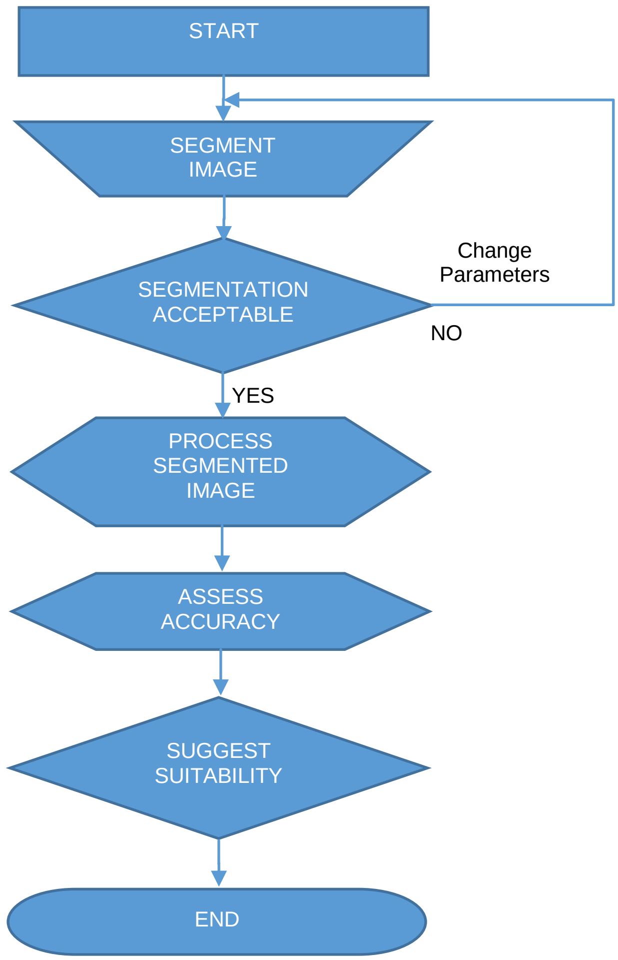


FIGURE 1: Experimentation Process.

4. EXPERIMENT RESULTS

Let us review the segmentation results which seem to be largely successful visually, but on few images only. The computed accuracy measures also indicate that the image segmentation has been quite successful / acceptable in most cases.

On some images though, either of the segmentation methods have not been successful. While we have presented few here, there have been much more images on which segmentation was conducted, but only select few have been presented here. These segmentations were the best possible as were observed during multiple segmentation runs for varied segmentation parameters.

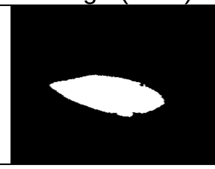
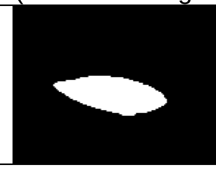
Original Image	Ground Truth	Segmented Image (SFM)	Segmented Image (Localized Region)
			
	Jaccard Index	0.9307	0.9125
	Dice Coefficient	0.9641	0.9542
	Hausdorrf Distance	3.8730	3.4641

TABLE 1: Segmentation Set 1.

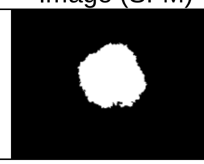
Original Image	Ground Truth	Segmented Image (SFM)	Segmented Image (Localized Region)
			
	Jaccard Index	0.9686	0.9620
	Dice Coefficient	0.9841	0.9806
	Hausdorrf Distance	3.3166	3.4641

TABLE 2: Segmentation Set 2.

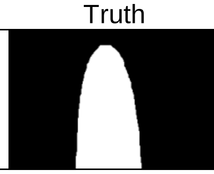
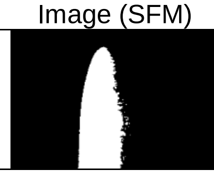
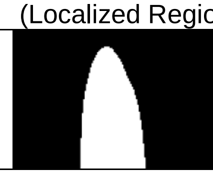
Original Image	Ground Truth	Segmented Image (SFM)	Segmented Image (Localized Region)
			
	Jaccard Index	0.6695	0.9410
	Dice Coefficient	0.8020	0.9696
	Hausdorrf Distance	5.1962	3.1623

TABLE 3: Segmentation Set 3.

In the below segmentation sets, none of the discussed methods have been fully successful as can be confirmed visually and hence accuracy measures have not been shown here.

Original Image	Segmented Image (SFM)	Segmented Image (Localized Region)
		

TABLE 4: Segmentation Set 4.

Original Image	Segmented Image (SFM)	Segmented Image (Localized Region)
		

TABLE 5: Segmentation Set 5.

Original Image	Segmented Image (SFM)	Segmented Image (Localized Region)
		

TABLE 6: Segmentation Set 6.

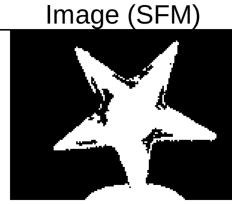
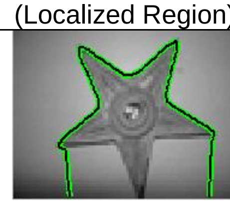
Original Image	Segmented Image (SFM)	Segmented Image (Localized Region)
		

TABLE 7: Segmentation Set 7.

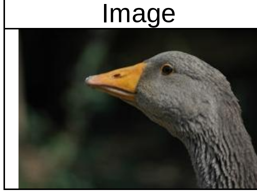
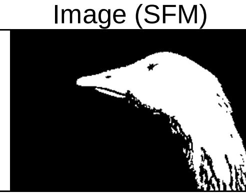
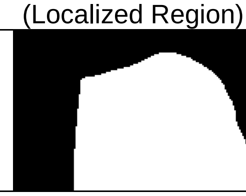
Original Image	Segmented Image (SFM)	Segmented Image (Localized Region)
		

TABLE 8: Segmentation Set 8.

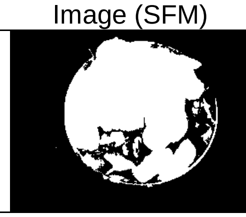
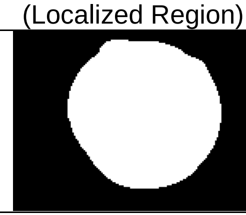
Original Image	Segmented Image (SFM)	Segmented Image (Localized Region)
		

TABLE 9: Segmentation Set 9.

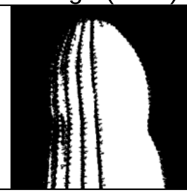
Original Image	Segmented Image (SFM)	Segmented Image (Localized Region)
		

TABLE 10: Segmentation Set 10.

5. OBSERVATIONS

Overall in this experiment, we found both the techniques to be quite slower when compared with [14, 15]. The iterations took bit longer to complete the segmentation even though the size of the image was reduced during segmentation to speed up the process. Localized Region based technique however was relatively faster amongst the two.

While the original images appear to have sufficient colour separation between the foreground and the background, the real challenge is faced when the images are converted into greyscale to prepare them for segmentation.

In the above segmentation set 1 and 2, as can be visually confirmed in the original image, the background and foreground object have very distinct colour, high intensity and very crisp object boundary separating from the background. The image segmentation is also quite acceptable, with one exception being that in the segmentation set 1, the Sparse Field Matrix method has marked few foreground pixels as background. Also, it is very evident that the object boundary has come out very nicely in Sparse Field Matrix as compared with Localized region based method. In the segmentation set 2, in the localized region based method, the edges have been lost (became smoother) during iterations, however, Sparse Field Matrix method has segmented the image better.

In the Segmentation set 3, as can be seen, the foreground object has not been extracted cleanly using Sparse Field matrix method. The sharp vertical intensity line along the object seems to be interfering with the segmentation process; whereas Localized region method has done a much better segmentation on the same input image.

In the segmentation sets 4 to 10, the images are quite complex and have similarity in foreground and background at few places in the image and/or there is sort of overlapping of colours belonging to foreground as well as background and neither of the two discussed methods could successfully segment the objects at an acceptable level. On some images Sparse Field Matrix method seems to have yielded better results and on other Region Based method.

Sparse Field Matrix method seemed to perform better in contrast with Localized regions based method, specifically on such images wherein foreground object is stretching up to the image boundary (see segmentation sets 7 and 8). Particularly in Segmentation set 7, the darker edges along the boundary seems to affecting the success of the Localized region based segmentation technique.

6. DISCUSSION

There has been research wherein various approaches to image segmentation have been studied as stated in [20, 21, 22] and it was observed that image segmentation techniques are highly application dependent. A recently done survey [23, 24, 25, 26], employed subjective comparison of various image segmentation algorithms using standard parameters such as processing speed, computation complexity, automaticity, noise resistance, multiple object detection and accuracy for Threshold, Region and Cluster based segmentation techniques. Therein, it was commented that certain techniques are faster while others provided more accurate results. In [27, 28], the authors have compared segmentation techniques and have proposed a hybrid approach for better results, again, evaluated the algorithms by comparing the running time, correctness, stability with respect to parameter choices and image choices, thereby prompting that segmentation algorithms alone may not lead to an output that can be directly fed to applications. It implies that combinational approach might lead to better segmentation results. Specifically in the field of medical engineering, there has been an excellent work [29] wherein the authors have objectively compared different segmentation techniques, using correlation and structural similarity index (SSIM) to ascertain suitability for the purpose. Specific to infrared images, there has been comparative work as explained [30] to ascertain suitability specifically for infrared applications.

A different approach to quantitative evaluation, using Normalized Probabilistic Rand (NPR) was employed by [31] to compare various algorithms to ascertain stability & accuracy on natural images. An excellent work and as explained in [32], various experiments were conducted to enumerate and review main image segmentation methods, presented basic evaluation methods and have discussed the prospect of image segmentation in detail. In another work [33], authors have used Bhattacharya Coefficient to measure similarity and went on to propose Similarity Region Merging as much better and effective segmentation method.

Another excellent work with detailed mathematical background on the assessment of evaluation methods by [34] actually delves deeper into subjective or supervised and un-supervised objective evaluation methods however, finds that we still need to make progress for the unsupervised methods to be successful on wide variety of natural images, taking further the works done in [21].

Experimental comparison with very detailed explanation between Graph Cut and variants of Active Contours is explained in detail in [35] and it has been observed that Active contours are often implemented with level set methods for their universality and performance, but disadvantage is their computational complexity.

In this experiment we have also observed that, although both the methods discussed are well known and have provided breakthrough in image segmentation challenges and while these techniques have been very effective on images which have very distinct or separable object boundary from the background, with higher intensity complimenting the segmentation process making it successful, however, these are not effective on images with complex composition.

7. CONCLUSION

Our study focused on two variants based on Level Sets technique, viz. Sparse Field Matrix and Localized region method. Sparse Field Matrix was found to be relatively slower than Localized Region Method. Localized Region based method seem to require initial mask to be placed outside the foreground object boundary in the image. As a result of this, when initial mask is not outside foreground object boundary, this method tends to have incomplete foreground object post completion of segmentation. This limitation does not seem to be applicable to the Sparse Field Matrix method.

Localized region method needs initial mask to be placed outside the foreground object and this could be limiting on all such images in which foreground object is touching the boundary of the image itself. However, where the foreground object edges are crisp this technique seems to score more than Sparse Field Matrix. Although these methods are great, these could not be generally applied to all the images involved in this experiment.

It is evident that the discussed methods might be suitable for low to moderately complex images only. Such Images which employ great deal of complexities, the accuracy of these techniques seems to be limiting. For specific applications, these methods alone may not be sufficient to achieve the desired result.

8. HIGHLIGHTS

While there has been lot of work in comparing or evaluating segmentation algorithms, which mostly is based on available literature and largely is in the form of surveys, with few studies taking a step further and have performed objective evaluation using one or two parameters (NPR or Bhattacharya coefficient). This study on the other hand has employed three statistical measures, to ascertain effectiveness with pointed observations.

This experiment, it establishes that both the discussed techniques are ineffective on images with higher complexities leading to unacceptable segmentation results and also reiterates that fully automatic segmentation techniques, even if those employ an initial seed, may not be successful on complex natural images. This experiment also suggests that segmentation techniques alone may not yield successful results on complex natural images and pre and post processing would be necessary to refine the output of the segmentation process for it to be acceptable in the applications. Combinational approach employing multiple techniques or methods seem to be more effective in the absence of general algorithm that can be applied on all images and the need to develop such an algorithm continues to exist.

9. FUTURE WORK

We intend to continue studying various algorithms and techniques by conducting similar experiments, to understand effectiveness and accuracy on various natural images using the same accuracy measures to maintain consistency and provide mathematical foundation to the assessment. During study and experimentation it will be observed and assessed, which algorithms are more suitable or effective for specific segmentation needs. We expect this research shall add value and assist fellow researchers since the recommendations are based on scientifically conducted experiments.

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