Segmentation of Cereal Plant Images Using Level Set Methods – A Comparative Study

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***Abstract*— In this paper we evaluate the quality of segmentation of plant images achieved by different level set methods commonly used in the literature. The plants of study are narrow-leaf cereal plants at different growth stages and the segmentation quality measure was considered to be the boundary, leaf tips, and axils. The results show that region-based level set methods can perform the segmentation of plants with high accuracy when the plants are at either early or mature stages of growth. The results also show that contour based level set algorithms are not applicable to the segmentation of narrow leaf plants because the front being computed does not advance to the high curvature features, such as sharp tips and axils. A typical image of a mature plant has isolated regions from the interlacing of leaves. Only region-based methods can perform the segmentation with good accuracy. Level set methods are sensitive to initialization and parameter selection.**

***Index Terms*— level set, active contour, image segmentation, narrow-leaf plants.**

I. Introduction

Locating and segmenting plants from the background in an automated way is a common challenge in the analysis of plant images. Segmentation is an essential preliminary to an effective identification or other post-processing step. Any post-processing such as textural analysis for crudely segmented images will yield unreliable results due to background features mixed with those of plants [1, 2]. Direct techniques such as pixel based classification methods rely on a single iso-value to represent the object of interest which may not segment real world images with good results. In addition, the intensity inhomogeneities, which occur in real-world images, cause these methods to segment a particular object of interest into several regions [3]. In contrast, level set segmentation techniques rely on other properties of the data such as intensity gradients or image variations in terms of color, texture and even motion to represent a particular boundary object [2-5]. Regardless of the properties of the image data, almost all level set methods rely on solving some first or second order partial differential equations (PDEs). These PDEs are based on the speed term, which is a function of the local, global and shape-independent properties of the boundary. Curvature is an example of the local property of the front. The global properties of the boundary depend on the shape and position of the front, and the properties which are independent of the geometry of the moving front passively inflate the boundary and image information such as pixel intensity and gradient. The speed related to the shape-independent properties is usually called ‘constant force’ or ‘balloon force’[6, 7].

There are a number of level set PDEs used in image processing and particularly used for image segmentation such as the segmentation of medical images. The results of image segmentation showed that most of the level set methods usually define the boundary of the objects in medical images with high accuracy[8, 9]. On the downside, the level set algorithms are usually computationally very intensive [10, 11]. However, a number of fast level set computation algorithms have recently been proposed [11-15]. The accuracy of most of these methods is very susceptible to the shape and placement of the initial contour, careful selection of parameters used in the PDE algorithm and the choice of stopping factor [16, 17]. This sensitivity issue is in addition to problems incurred due to discretization and calculation of curvature of the digitized curves. In the present paper, we review the performance of some recently developed level set PDE algorithms through application to the segmentation of narrow-leaf wheat plant images taken by a high-throughput imaging system.

II. Plant Image Segmentation

The narrow-leaf wheat seedlings were imaged every second day by cameras fixed in stations at the Australian Plant Phenomics Facility (APPF). Identification or extraction of any characteristics from the plants requires a good segmentation process. The APPF provides state-of-the-art plant growth environment and the latest technology in high throughput plant imaging for the repeated measurements of the phenotype of plants automatically and

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non-destructively. It can produce thousands of plant images by different cameras from different angles (two side views and a top view) in one day, so it is highly desirable to be able to process these images automatically.

The side view images provide more information, including the height of the plant. In these views, narrow leaf wheat plants usually appear with some sharp leaf tips and deep axils on the images either at their early growth stage or when they are fully mature, as shown in Fig.1.

Fig 1. Sample images of narrow leaf wheat seedlings at early stage of growth (Left) and mature age (Right)

The level set methods have been documented to produce good results on medical images for which the boundary of the regions of interest usually have low curvature values [6, 15, 18-23]. However, the main issue in employing the level set methods for segmentation of plant regions or capturing the boundary of the narrow leaf plants is the existence of many high-curvature features on the images of these types of plants. This is not the case for medical images The high curvature features of these plants (i.e. sharp tip and axils) prevent some level set methods from identifying and wrapping the level set around the sharp tips, and capturing the deep valleys between adjacent branches even with the best possible choice of parameters as shown in Fig.2.

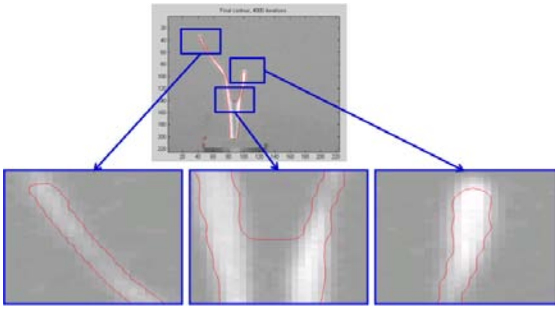

Fig. 2. The Fig. depicts evolving level set contour failing to capture both sharp leaf tips and the deep axils (high curvature regions) using the level set method described in [20]

III. Level set based boundary propagation

Level set techniques, or implicit active contours, have been used in a variety of applications including medical image processing [6, 15, 18-23], segmentation of two and three dimensional images [24, 25], motion analysis [21, 26] and image registration [27]. Level set segmentation involves solving the energy-based minimization problem by the computation of geodesics or minimal distance curves [28]. In this approach, a curve is embedded as a zero level set of a higher dimensional surface. The entire surface is evolved to minimize an energy metric defined by the curvature and image gradient [29]. In practice, the user specifies an initial contour, which then evolves toward the boundary by image driven forces defined in terms of PDEs [6, 30].

Suppose you are given an interface, which is on a 2D image the boundary between two separate and closed regions, or the interface is represented implicitly as the zero level set (or contour), ie. $C_0 = \{(x, y) \mid \varphi(x, y, t) = 0\}$, of a higher dimensional level set function φ, which varies with space and time (i.e. $\varphi = \varphi(x, y, t)$ in two dimensions). Over the rest of the image space, this level set function φ is defined as the signed distance function from the zero-th level set. Therefore, for a given closed curve the function is zero if the pixel is on the curve itself, otherwise, the function is $\varphi(x, y, t) = \pm\, d\,(x, y)$, where d is the minimum distance from the pixel to the curve; and the sign is negative for pixels inside C_0 and positive for pixels outside C_0 (Fig. 3).

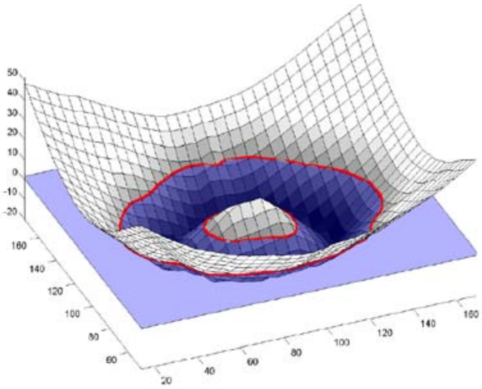

Fig. 3. Example of level set function and the zero level set which is represented as a red close curves as the intersection of the zero-th plan and the level set [23]

The function φ is then evolved in a direction normal to itself, and the level set method tracks the interface movement through the following equation

$$\frac{\partial \varphi}{\partial t} + F\|\nabla \varphi\| = 0 \qquad (1)$$

where $\varphi\ (x, y, t)$ is the level set function. F is the speed function, depending on the curvature, image data and the level set function φ. F can be a combination of a constant speed, F_0, which is sometimes called the balloon force and is independent of the geometry of the moving front, and F_1 which is the function of the curvature. In this way, the level set method converts the geometric problem into a partial differential equation, and enables the well established methods of partial differential equations to work in solving the geometric problem [14, 31].

IV. Reinitializiation of level set functions and signed distance function

As the front evolves, the PDE of (1) often deforms the level function in a way that its slope is too flat or too steep near the edge or the interface. In such cases, a small perturbation of the level function may result in a big change of interface location, and the level function may lose enough regularity near the edge and therefore the zero level set is not exactly at the boundary. One solution is to replace the level function with a better behaved function, the signed distance function to the interface [31, 32] and to periodically re-initialize the signed distance function [6]. The signed distance function is the minimum distance from each pixel in the image to the prescribed initial contour.

V. LEVEL SET ALGORITHM AND ENERGY FUNCTION

There are a number of level set methods developed for segmentation applications for ad-hoc medical images. However, almost all of these methods follow some common generic steps:

1. Placement of an initial contour (arbitrary, outside or inside the region of interest)
2. Level set φ = Signed Euclidean Distance Function of the contour
3. Function φ allowed to evolve according to first or second derivative PDEs
4. It is reinitialized after a number of iterations (= Signed Distance Function of the evolved contour) – Go to step 2
5. Until the function φ converges or = 0

The placement of the initial contour is still a key challenge in some level set segmentation methods. The contour can move inward or outward and the its initial placement determines the segmentation target [6]. In some methods, such as outlined in [3, 18], the initial contour is replaced with a region-based contour and the reinitialization step has been eliminated by including a term in the PDE that penalizes the deviation of level set function from a signed distance function. Steps 3 to 5 are in fact the process of minimizing some energy functional. Different level set methods differ either in terms of their initial contour or the energy functionals to be minimized or some combination of both. There are still key challenges in this area and there is no general level set method that works for all applications. For different applications, a number of PDEs can be used and the solutions of PDEs are susceptible to the choice of the parameters appearing in the energy functional.

VI. SELECTED LEVEL SET METHODS FOR THIS STUDY

For this study, we compare the level set methods described in [3, 5, 20, 33-35]. The comparison measure is the quality obtained of the plants edges particularly at leaf tips and at where the leaves joining to the plant stem.

The level set method in [20] uses the steepest descent process for minimization of the following energy functional:

$$\frac{\partial\varphi}{\partial t} = \mu[\Delta\varphi - \mathrm{div}(\frac{\Delta\varphi}{|\Delta\varphi|})] + \lambda\delta(\varphi)\mathrm{div}(g\frac{\Delta\varphi}{|\Delta\varphi|}) + vg\delta(\varphi)$$

$$\delta_\varepsilon(x) = \begin{cases} 0 & |x| > \varepsilon \\ \frac{1}{2\varepsilon}[1+\cos(\frac{\pi x}{\varepsilon})] & |x| \le \varepsilon \end{cases}$$

where φ is the evolving contour, δ is the smoothed Dirac function approximated by $\delta_\varepsilon(x)$, g is the edge indicator function, which is a reverse function of the intensity image convolved with Gaussian kernel with σ standard deviation; μ is the level set regularization parameter and λ and ν are constants.

The first term is the regularization term which controls the effect of penalizing the deviation of the contour from the signed distance function. Therefore the evolving contour does not need to be reinitialized after a certain number of iterations. The second term in fact represents the length of the contour and the third term represents the area of the inside of the contour. The second and third terms correspond to the gradient flow of the energy functional which is driving the zero level contour towards the object boundary. For a particular application, there are six parameters σ, ε, μ, λ, ν as well as the number of iterations that are required for this method to achieve good segmentation results.

Li's method in [3] is also a level set without re- initialization process. The same level set regularization term is used here to force the level set contour to be close to the signed distance function. However, unlike [20] the initial contour is estimated from a region-scalable fitting that locally approximates the image intensities on the two sides of the contour.

The Chan and Vese model is also described as a region-based level set method that tends to separate the image into two homogenous regions [35]. It uses the same second and third terms in the PDE equation of [20] with additional terms described in the following evolution equation:

$$\frac{\partial\varphi}{\partial t} = \delta(\varphi)[(I-\upsilon)^2 - (I-u)^2] + \lambda\delta(\varphi)k$$

where, similarly to [3], I(x) is the edge indicator defined by a positive and decreasing function, depending on the gradient of the smoothed image by a Gaussian filtering, k is the curvature. For this method, there are also certain parameters which require to be specified for a particular application.

The next method is the geodesic active contour developed by Caselles [33]. This model is a contour based method employing the gradient of the image is to make the contour move towards the boundary. The PDE used in this method is given as:

$$\frac{\partial\varphi}{\partial t} = g(I)\,|\nabla\varphi|\,div(\frac{\Delta\varphi}{|\Delta\varphi|}) + \nabla g(I).\nabla\varphi$$

where $div(\frac{\Delta\varphi}{|\Delta\varphi|})$ is the curvature (k), φ is the evolving contour, I is the image intensity and g(I) is the edge indicator of the image I defined by a positive and decreasing function, depending on the gradient of the image smoothed by Gaussian filtering. This method does not require any re-initialization. The level set computed by this method is based on the narrow band of the level set. It is very slow and sensitive to initialization.

Lankton et al [5] developed a region-based level set method in which the foreground and background are statistically modeled in terms of smaller local regions and an energy optimum is found where the model best fists the image. Analysis of local regions results in the creating a series of local energies at each point along the curve, and each point moves separately to optimize the local energies. Taking the first derivative of the final energy functional gives us the following evolution equation:

$$\frac{\partial\varphi}{\partial t}(x) = \delta\varphi(x)\int B(x,y).\nabla\phi(y)F(I(y)\phi(y))dy + ...$$

$$\lambda\delta\varphi(x)div(\frac{\Delta\varphi(x)}{|\Delta\varphi(x)|})$$

where I denotes a given image, □ is the direct function, F is a generic internal energy measure, and B is used to mask local regions and defined in terms of a radius parameter of r as below:

$$B(x, y) = \begin{cases} 1 & \|x - y\| < r \\ 0 & otherwise \end{cases}$$

The function φ is implemented as a signed distance function and is reinitialized at each iteration. The Lankton's method has four specific parameters required to be specified: the feature type, the neighborhood type, the curvature term □, and the radius term[5].

Bernard's method [34] is a region-based method that partitions an image into two homogenous regions according to their mean value of intensity. In this method, the implicit level set function is expressed as a linear combination of B-Spline basis functions:

$$\varphi(x) = \sum_{k \in Z^d} c[k]\beta^n(\frac{x}{h} - k)$$

In this expression $\beta^n(.)$ is the uniform symmetric d-dimensional B-Spline of degree n. This algorithm also has some specific parameters to be modified for different applications.

VII. EXPERIMENTAL RESULTS AND DISCUSSION

It is worth noting that before applying any of the level set methods to our APPF plant images, a correction for lens distortion was introduced in the images using an algebraic approach described in [36].

The plant boundary obtained by the method described in [20] is not accurate; the boundary rounds off the leaves' sharp tips and bypasses the sharp corners and fails to extend into the axils (Fig. 4). In addition, as it is a contour based method, it is very slow in processing.

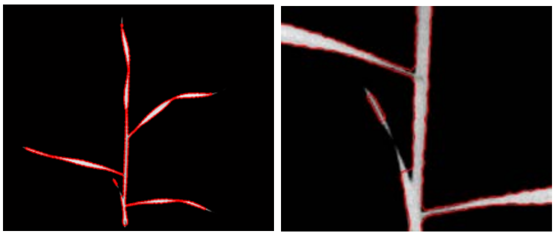

Fig. 4. Results for the plant image segmentation using the level set method by [20] after 2200 iterations (Left); close-up showing some missed sharp tips and undetected axils (Right)

The method in [3] can segment the plant from the background reasonably well when the initial region is either small enough to fit inside the object or when fifty percent or more of the initial region fits inside the plant (Fig. 5)

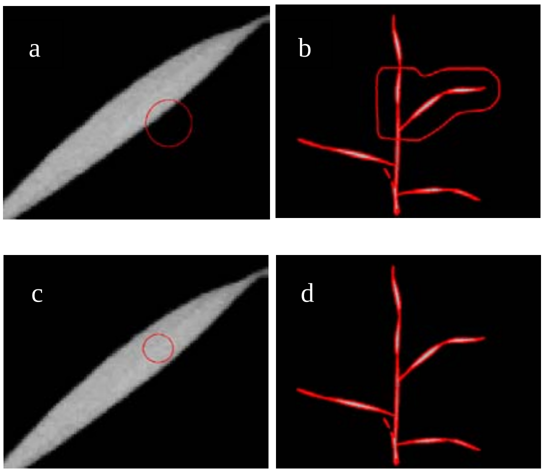

Fig. 5. Results for the plant image segmentation using the level set method of [3] with μ =0.03 , σ = 15 and number of iteration of 200; initial contour mostly outside the region of interest and the result of segmentation (a, b); the initial contour inside the region of interest and the result of segmentation (c, d)

Fig. 6 illustrates the segmentation results of using the contour-based level set method described in [33]. Notice that the plant region can be easily segmented after 1700 iterations using this method. In this method, the initialization begins from outside of boundary. A parameter represents the degree to which the constant force pushes the contour inwards or outwards independently from the geometry of the boundary; negative when the contour is supposed to move inwards (initial contour outside of the boundary) and positive when the contour is pushed outwards (initialization begins from inside out). As with the other contour based method, [3], the sharp leaf tips are rounded and bypassed using this method as well and the contour does not extend into the axils, no matter how carefully one selects parameters and regardless of the number of iterations (Fig. 6 - right).

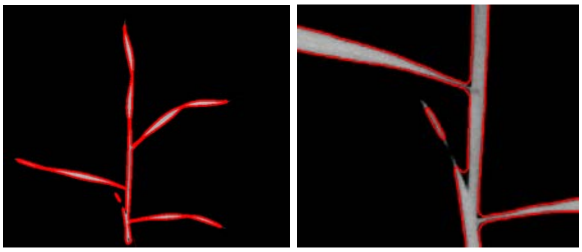

Fig. 6. Results for the plant image segmentation using the level set method by [33] after 1700 iterations (Left); close-up showing some missed sharp tips and undetected sharp valleys (Right)

A sample of the segmentation results obtained from Lankton's method is shown in Fig. 7. As can be seen, the resulting contour is smooth; however, it has bypassed the edge of the narrow part of the leaf blades. Also, the regions with large mean curvature, i.e. sharp tips and axils, also have been rounded. This is likely because these high curvature features have high energy resulting from the second term in the evolution equation.

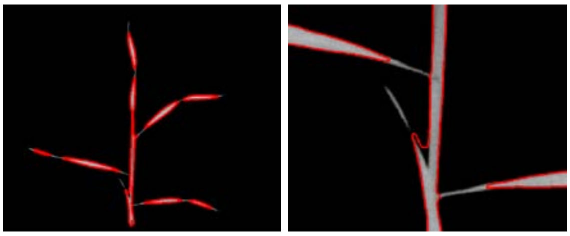

Fig. 7. Results for the plant image segmentation using the level set method by [5] after 200 iterations (Left); close-up showing some bypassed narrow parts of the leaves, missed sharp tips and undetected axils (Right)

Bernard's method [34] produced very good results. Because this method is region-based, regardless of initial contour it segments plant images into plant and non-plant regions which is the aim of the segmentation (Fig. 8a). In addition, this method is very fast in terms of processing speed. This algorithm has a few specific parameters such as a smoothness factor, which is required to be set. For instance, if the smoothness factor is not set properly the edge will not be close to the boundary (Fig. 8b).

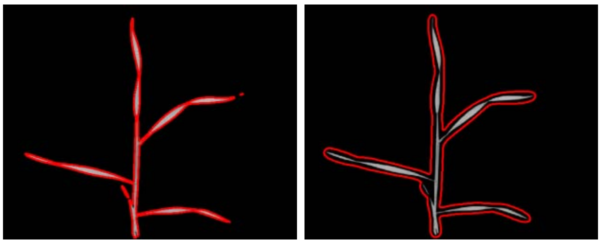

Fig. 8. Results for the plant image segmentation using the level set method by [34] just after 10 iterations with the degree of smoothness of 1 (Left) and the degree of smoothness of 3 (Right)

Among these methods, only Li's method and Bernard's method could segment relatively well when plants are at a mature age, while contour based methods such as Caselles' fails to pick out the plant region due to the isolated background regions created by crossing and overlapping leaves (Fig. 9). Although Bernard's method [34] was faster, it did not pick some of the sharp axils and some holes perfectly and while Li's method [3] was much slower, it detected these features with good accuracy (Fig. 9). It is worth noting that even with these methods, the required parameters appearing in PDEs should be selected very carefully: if not, the segmentation performance degrades significantly.

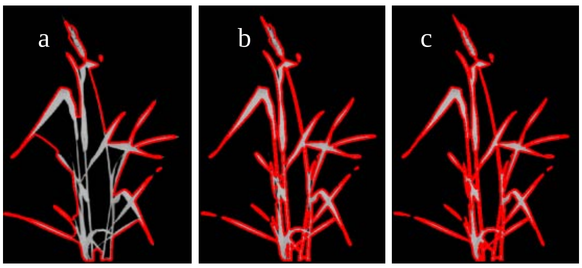

Fig. 9. Results for the image segmentation of a mature plant a) undetected holes in the middle of the plant by contour based method of Caselles [33] after 1200 iterations; b) undetected sharp valleys and small holes by Bernard's method [34] evolving stopped after 7 iterations; c) results form Li's method [3] after less than 200 iterations

VIII. LEVEL SET LIMITATIONS

The region-based methods can segment plants from image backgrounds with relatively high accuracy when only two distinct regions are available in the images: plant and background regions. However, when the images contain additional non-plant objects (in our case, such as pot, pot holder and the conveyor mechanism, etc) even the most accurate level set models fail to extract the plant region (Fig. 10).

A possible method to fix this problem is to use the background estimation method based on motion detection techniques using only two images; that is, two images taken of two plants at different times with the pot, pot holder and conveyor mechanism appearing relatively on the same position on the images. The method is described in [36]. Once the background is learned by this method, the background image (with all non-plant objects) is subtracted from the image of plant and non-plant objects. As a result, the image is partitioned into only two plant and non-plant regions. Now, the boundary of the plant can be refined by applying a level set method on this two region image (Fig. 10). This is a future work planned to be carried out by the authors.

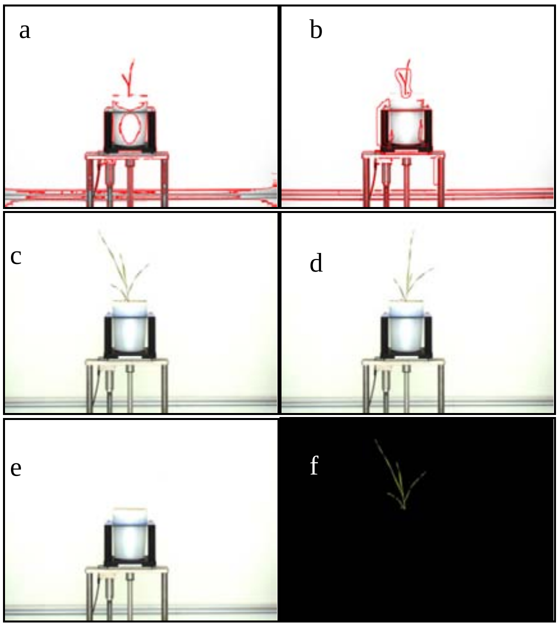

Fig. 10. a, b) results of level set segmentation of the image with plant and more than one distinct non-plant objects using [34] and [3], respectively (c, d) two images used in background estimation method described in [36]; e) the resulting background; f) roughly two-region image which is the difference of image c and background image f

IX. CONCLUSIONS AND DISCUSSIONS

We compared different level set methods for the segmentation of the images of narrow leaf plants. The narrow-leaf plant images are different from medical images in the way that the narrow leaf plants have high curvature features at the tips and axils. The leaves of the mature plants overlap and develop sharp corners and holes which make these features hard to detect.

Experimental results for plant images showed that using the region-based level set methods have advantages over contour-based level set methods for segmentation of images with two distinct regions of plant and non-plant regions. The advantages include faster convergence, robustness against initial contour placement and insensitivity to image noise, as also suggested by [5]. Among the region-based methods, a compromise is required between achieving high accuracy or low processing speed. All the above methods, however, might not produce good results when there is more than one distinct non-plant object in the images. For these cases, applying a background learning method will provide an opportunity to segment plant objects whose boundaries can be refined by the level set methods.

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