# A Leaf Vein Extraction Method Based On Snakes Technique

YunFeng Li QingSheng Zhu YuKun Cao ChengLiang Wang
Department of Computer Science and Engineering, Chongqing University, Chongqing, 400044, P.R. China
lyf129@126.com

***Abstract*—Leaf vein extraction is a key step of modeling plant organs and living plant recognition. An efficient leaf vein extraction method is proposed in this paper by combining snakes technique with cellular neural networks (CNN). The active contours technique based on CNN provide high flexibility and control for the contour dynamics of the snakes. This approach has the advantage of applying a priori knowledge, puts similar characteristics from both the implicit and parametric models, to improve the precise and robustness of the segmentation. The experimental results have also shown that the proposed method can obtain satisfactory results of leaf segmentation (to extract leaf veins and outlines), for the subsequent modeling leaf and leaf recognition.**

## I. INTRODUCTION

Leaf vein extraction is a key step of modeling plant organs and living plant recognition. Plants have complex structures. Computer graphics research has produced many models of plants and simulated the growth processes of plants. In contrast to the extensively researched modeling of plant architecture, the modeling of plant organs has so far remained relatively unexplored. One of the challenges in computer graphics is to create the geometry of objects in an intuitive and direct way, while allowing for interactive manipulation of the resulting shapes. This is particularly important in the synthesis of realistic images of plants, where a detailed representation of a plant component's shape is vital in capturing the character of a species. In Refs [1], the authors presented an interactive method for modeling leaf by using image and biological data for each individual plant. Undoubtedly, Leaf vein extraction is an important part of modeling plant organs. Assessing the appearance of plants is an important botanical skill, with many applications, ranging from plant recognition to health diagnosis. In identifying plant species, human beings will observe one or more of the following: the whole plant, leaves, flowers, stem and fruit. Plant leaf has an approximately two-dimensional nature. Therefore, it is most suitable for machine processing. As the shape of leaves is one of the most important features for characterizing various plants visually, and the study of leaf segmentation will be an important stage for developing a plant recognition system [2].

In recent years, various approaches have been proposed for characterizing plant leaf. However these methods mostly concentrated on the peripheral contour representation and the recognition of the leaf. It is not enough to involve leaf segmentation by edge detection. Most edge operators such as Sobel, Prewitt, Laplacian, focused on inspecting the locations in an image where a sudden variation in the grey level or color of pixel appears. For leaf vein extraction, which contains the important information for plant species, some vein pixels belong to edge pixels, while others are at the locations where the grey level varies very smooth. The width of a vein often contains several pixels. Furthermore, the width of the vein is very essential to distinct the main vein from the accessory veins. In [3], a two-stage approach for leaf vein extraction is proposed.

Image segmentation techniques by means of deformable templates (or called active contours), are an interesting approach among segmentation methods. Kass et al. (1988) first studied the concept of active contour or snake, in order to overcome problems in classical edge detector methods [5]. The approach had an initial model (contour), which was deformed until reaching a fine location guided by both external and internal forces. And it is successfully applied in biomedical image processing, such as the segmentation of anatomical structures, due to its ability to exploit the mixed control bottom-up and top-down (prior knowledge). The main drawback of classic snakes segmentation comes from that they need at some extent, a high computational effort, which restrict them inappropriate for applications needing fast response. Mcinerney et al. (1995) investigated a new parametric model (called T-Snakes) including the additional procedure of reparameterizing the geometric model during the deformation [6]. One different alternative to the basic snakes is the implicit models [7]. The method consists of independent strategies based on the wave-front propagation with velocity depending on the curvature. In [9], the author designed an active contour technique based on CNN. This methodology puts similar characteristics from the parametric and implicit deformable models in both the contour evolution process and the mechanisms for the contour guide. And the implementation of this active contour approach as integrated circuits would allow to the massively parallel processing in CNN to reduce processing time.

This paper designs an efficient leaf segmentation method by combining snakes technique with CNN. The active contours technique based on CNN provides a high flexibility and control for the contour dynamics of the snakes. This model evolution is based on color information of leaf image.

This approach has the advantage of applying a priori knowledge, to improve the precise and robustness of the segmentation. The paper is organized as follows. Section 2 describes the active contour technique based on CNN. In Section 3, the proposed method is given. The conclusions are summarized in Section 4.

## II. THE ACTIVE CONTOUR TECHNIQUE BASED ON CNN

The principle of active contour consists of seeking the best adjustments to a model of the contour of an image, in terms of position, orientation, and eventually deformation, with respect to layer transitions in the image. The external forces lead the snake towards features of the image, whereas internal forces model the elasticity of the curve. This adjustment is managed by minimizing of an energy term E, which is made uo of two factors: $E_{int}$ is referred to internal constraints of the model (internal energy of the model), $E_{image}$ is referred to image features(external energy), as

$$E = \int_0^1 (E_{\text{int}}(v(s)) + \lambda E_{image}(v(s)))ds$$

where v(s)=(x(s),y(s)) is the model contour in pixels and $\lambda$ is a weighting coefficient. The internal energy by imposing continuity and smoothness on the model and taking into account the curvature and the length of the contour, is often defined as

$$E_{\text{int}}(v(s)) = \alpha\left|v_s(s)^2\right| + \beta\left|v_{ss}(s)\right|^2$$

where $\alpha\left|v_s(s)^2\right|$, which weights its resistance to stretching to stretching. $\beta\left|v_{ss}(s)\right|^2$, which weights its resistance to stretching to bending. The elasticity parameters $\alpha$ and $\beta$ control the smoothness of the curve. The external energy $E_{image}$ depends on the desired adjustment. For the model to be attracted by the contours, it is a function of the norm of the gradient in the image. If the object delimited by dark lines, it is a function of the intensity. In the same way, there are many other examples of using information, such as texture or color of the object, or regional properties. A typical expression of the external energy are:

$$E_{image}(v) = \int_0^1 P(v(s))ds \; ; \; P_I = \pm I(v(s))$$

where I is the intensity image, and attracts the curve to high or low intensity points.

$$P_G = -\left|\nabla(G_\sigma(v(s)) * I(v(s)))\right|$$

where $G_\sigma$ is a Gaussian filter with a scale parameter $\sigma$, and attracts the curve to intensity edges, after convolution with Gaussian smoothing; and

$$P_E = -e^{-d(v(s))^2}$$

where d(v(s)) is the distance to the closest boundary point, which pushes the contour to edge points of an edge map(An edge map is an image of contours detected by means of an edge detector filter).

Based on the calculus of variations, the contour v(s) which minimizes the energy E have to satisfy the Euler-Lagrange equation:

$$-\frac{\partial}{\partial s}(\alpha \frac{\partial v}{\partial s}) + \frac{\partial^2}{\partial s^2}(\beta \frac{\partial^2 v}{\partial s^2}) + \nabla P(v(s,t)) = 0$$

The curve v(s)=(x(s),y(s)), $s \in [0,1]$ is represented in terms of linear combinations of basis function. Most of methods are based on local-support basis functions like the finite differences method, the finite elements method and the B-splines. Nevertheless, most of segmentation methods on the basis of snake involve, to a greater or lesser degree, a high computational cost. Zhu and Yan proposed the minimization of the energy by using a Hopfield neural network [10]. But, due to the parametric nature, the method can't split a snake or merge two of them into one. An alternative to the parametric models is the implicit formulations [5]. The evolving snakes are defined as the zero level-set of a higher dimensional function. The evolution of the embedding function $\varphi$ are defined as

$$\frac{\partial \varphi}{\partial t} + g[F_I(k) + F_A]|\nabla \varphi| = 0$$

where $F_I(k)$ is a speed function depending on the curvature k which a similar regularizing effect as the thin-plate energy in parametric models. $F_A$ is an advection term independent of the moving front's geometry. The g(x,y) is a speed function normally decreasing with the image gradient establishing the stop criterion of the evolution. The evolution of the zero level-set, $C(s,t) = (x \mid \varphi(x,t=0))$ is given by

$$\frac{\partial C}{\partial t} + g[F_I(k) + F_A]\vec{n} = 0$$

where $\vec{n}$ is the inward normal to the curve. In [7], the authors proposed the geodesic active contours, which include a new component in the curve velocity leading the contour evolution towards minimal distance curves in a Riemannian space derived from the image.

In [9], the author proposed a DTCNN-based model and applied to active contours. The approach is adapts to handle the topologic transformations among contours dynamically by predicting the possible collision between them and carrying out a controlled split and merge of the contours by only local operations. The active contour by using CNN is based on iterative processes of expansion of the contour and its subsequent thinning by local information. Two steps are iteratively repeated for each cardinal direction in image plane (north, east, south and west). The information of leading snake has to be derived from external information previously extracted from the processing image, internal energy extracted from the contour itself in a dynamical process. The complete iteration can be reached after the processing along four cardinal directions. Every snake consists of a set of black pixels into a binary image called snake image. The external information is given by an array with real values called the external potential image whose size coincides with that of the image. The initial snake image and the external potential image represent the inputs to the network structure. The structure is constructed on bidimensional DTCNN. Every DTCNN block is made up of an array of cells with the same size of the image being treated. The equations, which decide the behavior of a DTCNN block, are defined as:

$$x_{(i,j)}(n+1) = \sum_{(k,l)\in N_r(i,j)} A_{(i-k+rj-l+r)} y_{(k,l)}(n) + \sum_{(k,l)\in N_r(i,j)} B_{(i-k+rj-l+r)} v_{(k,l)}(n) + I$$

$$y_{(i,j)}(n+1) = \mathrm{sgn}(x_{(i,j)}(n+1))$$

where $N_r(i,j)$ fixes the neighborhood topology with r a positive integer number. Matrices A and B represent the set of coefficients which weight the influence of outputs ($y_{(i,j)}$) and inputs ($v_{(k,l)}$) of the neighboring cells into the state of the cell according to ($x_{(i,j)}$). These matrices together with the offset term I are called templates. Templates are usually derived by design or learning. The design means that the desired function to be performed could be translated into a set of local rules. The learning is based on pairs of input and corresponding output signals.

## III. THE PROPOSED METHOD OF LEAF VEIN EXTRACTION

The snakes have been successfully used in image segmentation, medical imaging, face recognition and object recognition tracking. In [12], the author had applied the deformable templates to leaf shape segmentation. The method uses deformable templates, which locate the edges of leaves in the image, to provide an approach, which is as global and adaptable as possible. This method has given some satisfactory results when applied to green foxtail. Leaf vein extraction is different from the edge detection. Only the information of edge is not enough to segment the real modality of veins. The aim of the paper is to extract leaf veins and leaf outlines, for the subsequent modeling leaf and leaf recognition. Firstly, the input leaf images must be segmented into the leaf and the background. A preliminary segmentation based on the intensity histogram of image is carried out to get rough regions of leaf pixels. Then the active contour technique based on CNN is used to extract leaf veins in the obtained rough regions of leaf pixels.

The choice of the guide characteristics is a critical condition for the application of the active contours to specific tasks. Color characterization is important information of leaf image. The RGB colors are mixed to produce the various colors of the image. For their strong mutual relation, the RGB components are difficult to handle in the image-processing algorithm. Consequently, many image-processing applications use the hue, saturation and intensity (HSI) color model, and we use the intensity of HIS color model that is derived from the original RGB image. The transformation is defined as follows:

$$\begin{cases} H = \cos^{-1}\{\frac{[(R-G)+(R-B)]/2}{[(R-B)^2+(R-B)(G-B)]^{1/2}}\} \\ S = 1 - \frac{3}{R+G+B}[\min(R,G,B)] \\ I = \frac{(R+G+B)}{3} \end{cases}$$

In order to characterize the leaf veins color, leaf veins areas are selected in the image, and their mean and covariance are calculated in HIS model. For each pixel of the image, the Mahalanobis distance $d_c$ from the leaf vein color class (covariance C and mean u):

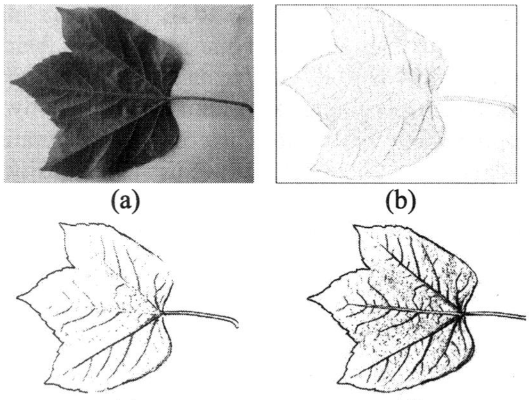
$$d_c^{\,2} = (x-u)^T C^{-1} (x-u)$$

where T denotes the transpose of the bracketed expression. This distance definition is used for the model evolution. Because the gradient forces is insufficient, this approach use the algebraic intensity depends on the color of the pixel in the image: $I_C = d_c - s$; where s is the threshold. The external potential associated with each pixel of leaf image is defined as:

$$E(x,y) = \alpha I_c(x,y) + \beta\left|\nabla G\sigma(x,y) * I_c(x,y)\right| + \gamma e^{-d(x,y)^2}$$

Where d(x,y) denotes the distance between the point (x,y) and the closest border in image processing. $\alpha, \beta, \gamma$ are constants that weight the contributions of each term.

A leaf image (Fig. 1(a)) is processed by the proposed method and the result is illustrated in Fig.1(d). Fig. 1(b) is the result of Edge extraction using Laplacian, and Fig. 1(c) as the result of edge extraction based on adaptive threshold. Perceptually, the proposed method produces better results than that of conventional edge detectors. Using the proposed method, the vein pixels both at the edge and within the veins are detected, which could lead to an easy and robust veins extraction even if a certain amount of vein points are missing. On the contrary, the results of edge detectors contain only the edge pixel of veins, which is not adequate for vein extraction that it is very sensitive to the false detection, such as the missing vein edge points, due to the difficulty in connecting discontinuous. A connectivity analysis can partly solve the question. This approach has the advantage of applying a priori knowledge, puts similar characteristics from both the implicit and parametric models, to improve the precise and robustness of the segmentation. Furthermore the model of CNN permits a VLSI implementation. So the proposed method is suitable for real-time applications.



(a) (b) (c) (d)

Fig. 1. The results of a Leaf vein extraction. (a) Original leaf image; (b) Edge extraction using Laplacian; (c) Edge extraction based on adaptive threshold; (d) The proposed method.

## IV. CONCLUSIONS

Leaf vein extraction is an important and key step of modeling plant organs and living plant recognition. The active contours have been successfully used in image segmentation, medical imaging, face recognition and object recognition tracking. This paper studied a leaf segmentation method by combining snakes technique with CNN, whose aim is to extract leaf veins and leaf outlines. This model evolution is mainly based on color information of pixel in leaf image. This approach has the advantage of applying a priori knowledge and fast response time, to improve the precise and robustness of the segmentation. The experimental results have also shown that the proposed method has achieved better segmentation results than traditional methods.

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