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Segmentation of Cotton Leaf Images using Parametric Deformable Model

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Abstract*: In this paper, the segmentation of cotton leaves from the complex background has been carried out using deformable model. In order to segment, a database of about 300 cotton leaves image was developed. The collected images were resized to 256x256 size. The resized image has been segmented using Adaptive Diffusion Flow (ADF) model. The ADF model has been obtained by replacing the smoothening energy term of gradient vector flow model with active hyper surface harmonic minimal function used to keep away from weak edges leakage. The infinite Laplace function is used to move the deformable model into narrow concave regions. Further, the developed model has been compared with the gradient vector flow and vector field convolution segmentation methods in terms of number of iterations, time taken for segmentation and various performance parameters namely precision, recall, Manhattan, Jaccard, Dice. From the results, it is concluded that the adaptive diffusion flow method is faster and performance parameters are better than the Gradient Vector Flow (GVF) and Vector Field Convolution (VFC) methods.

***Keywords* : Deformable model, gradient vector flow, vector field convolution, adaptive diffusion flow.**

I. INTRODUCTION

More than the 70% of Indian population is dependent on agriculture in general and 40% of cotton crops in particular. The cotton plant suffers from multiple diseases that can reduce the quantity and quality of yield. Mannually detection of diseases of cottan leaves can be done by ontinuous monitoring, which is not possible in larger area forms. In order to overcome this problem, an automatic detection of diseases in cotton plant can be dveloped [1,2,3]. Which can be used for early detection of diseases and plays important role in monitoring & suprvising the larger rop fields. In order to automatic detection of diseases, the segmentation of cotton plant leaves from the background is an important stage to obtain biomass characteristics [4], crop disease monitoring [5], crop disease recognition [6], etc.

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The number of methods for leaf segmentation have been proposed based on different techniques such as threshold-based[7], clustering[8] , wavelet, edge- based etc. To obtain biomass characteristics of plant leaves, segmentation is important. Accurate segmentation of leaves is a challenging task. The resultant image will help in accurately classifying the crop, crop growth status monitoring, and crop disease identification. Thi-Lan Le et al, proposed a plant identification method that uses an interactive segmentation method using a mobile device. It helps to extract leaf from the background using the watershed algorithm. To construct a scale and rotation invariant descriptor for leaf identification author introduced two improvements in kernel descriptor. Jonas De Vylder et al[8], leaf segmentation have been performed using active contour. The author introduced an automatic parameter setting based on the probability distribution instead of trial and error methods. The probability distribution was learned from the training dataset. Esmael Hamuda et al[9], presented a comparative study of various plant-based segmentation methods. Basically they concentrated on various plant extraction algorithms mainly on color index-based approaches. Manual Grand Brochier et al[10], discussed the comparative study of various segmentation methods for extracting leaves from natural background. The experiment was performed on 232 tree leaves with a complex background. Nearly 13 methods are considered for the comparative study and highlight among all those methods was the Guided Active Contour. Zhibin Wang et al[11], proposed a method for the segmentation of the overlapping leaves using combination of Sobel operator and level set method. The overlapping of leaf images extracted from the complex background and it was achieved by extracting only the interesting leaf region component from the image. Later, a single leaf was extracted from the overlapping of leaf images by combining the Sobel operator and level set method. There are different leaf segmentation techniques in literature[12]. This paper is structured as follows: Section 2 describes the background of various active contour algorithms; section 3 explains about the three methods used for comparison; section 4 discusses absout the results and discussion.

1. BACKGROUND

The different segmentation algorithms are available for the leaf segmentation.Out of which the active contour method is to be considered as the most suitable algorithm for the segmentation. Which has advantages like simple in implementation, low cost and faster in convergence. Active contours or snakes were first introduced by Kass et al[13], which is based on energy minimization spline that gets attracted to the edges of the image.

There are two different types of active contours namely parametric and geometric. Parametric active contours are based on the parametric curve which moves based upon the internal and external forces; whereas geometric active contour depends upon the geometric properties of the curve. The parametric active contour has two forces namely internal energy and external energy. The energy equation is given by equation 1:

$$E_{snake} = \int_0^1 \left[E_{int}\left(v(s)\right) + E_{ext}\left(v(s)\right)\right] ds \qquad (1)$$

Where E_{int} is the internal energy and E_{ext} is the external energy. By minimizing the energy function given by equation (1). which can be done by making external energy equal to internal energy, so that snake deforms towards the boundary of the object in the image.

The internal spline energy is given by

$$E_{int} = (\alpha(s)|v_s(s)|^2 + \beta(s)|v_{ss}(s)|^2)/2 \qquad (2)$$

From equation (2), it shows that the internal energy is responsible for determining the smoothness and continuity of the curve. The external energy drives the curve towards the boundary of the object. The problem with the traditional active contour is that it can not move towards concavity of an image. Sometimes the forces may not be enough to attract the edges of the images. İn order to overcome these difficulties, there are different external forces introduced like Gradient Vector Flow (GVF)[10,11], Vector Field Convolution (VFC) and Adaptive Diffusion Flow (ADF)etc. The details of these methods are discussed in next section.

II. METHODOLOGY

In this section, details of the methods are discussed as follows:

1.1. Databases

The database of 300 cotton leaves images has been developed by acquiring images from the agriculture field with background of soil and stones with the help of the digital camera. The acquired images are color images and are of high resolution 6000x4000 pixels with different regions and different shapes. The samples of acquired images of cotton leaves are as shown in Figure 1(a) and 1(b).

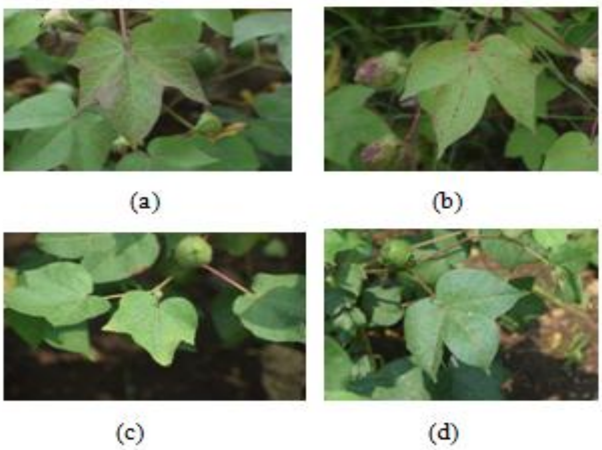


Fig 1: Sample of acquired cotton images

3.2 Pre-processing

The acquired images can't be used as it is for the segmentation of leaves. In order to segment leaf images from the background, preprocessing has carried out. In the preprocessing, the high-resolution images were converted into a standard size of 256x256 pixels. Furthur the resized image is converted into grayscale image and gaussian filter is used for removing the noise.

3.3 Segmentation

Finally, the pre-processed has been segmented by applying three deformable models namely Gradient vector flow, vector field convolution and adaptive diffusion flow models. The details of the results are discussed in the next section.

3.3.1 Gradient Vector Flow

The Xu and Prince [13,14, 15] introduced the new external force based on gradient vector field which is given by$V(x,y) = [u(x,y)\ v(x,y)]$ is responsible for minimization of energy function given by

$$E_{GVF} = \iint \mu\left(u_x^2 + u_y^2 + v_x^2 + v_y^2\right) + |\nabla f|^2 |V - \nabla f|^2 dxdy \qquad (2)$$

The above equation GVF field can be solved using Eulers Lagrange is given by equation (3) and equation (4).

$$\mu\nabla^2 u - (u - f_x)(f_x^2 + f_y^2) = 0 \qquad (3)$$

$$\mu\nabla^2 v - (v - f_x)(f_x^2 + f_y^2) = 0 \qquad (4)$$

The second term in the above equation (4) equals to zero, when the gradient of f(x,y) becomes zero. The GVF field is obtained by the above equations (3) and (4) with v(x,y) acts as an external force. This GVF field solves the problem of adequate capture range and the ability to move towards boundary cavities. But it has some limitations such as weak edge leakage, large computational time, sensitivity to noise, limited to capture range and ambiguity with other parameters. In order to overcome this vector field convolution has been developed.

3.3.2 Vector Field Convolution

The vector field kernel has been defined by

$$k(x,y) = s(x,y) + t(x,y) \qquad (5)$$

and all vector points at the origin is given by k(x,y) = m(x,y)n(x,y). where m(x,y) stands for magnitude of vector at (x,y) and n(x,y) is a unit vector pointing to the origin n(x,y)=[-x/r,-y/r]. where r represents distance from the origin except at origin is given by $r=\sqrt{x^2+y^2}$. This external force has a property a free particle placed in the field would be able to move towards the feature of interest like edges. The VFC[16] is given by computing the convolution of vector field kernel and edge map generated from the image is given by

$$v(x,y) = f(x,y) * k(x,y) \qquad (6)$$

where f(x,y) is an edge map, k(x,y) is a vector field kernel and * denotes convolution. The edge map is larger at nearer image edges and it contributes more to the homogenous region. Therefore, VFC external force can move free particles to the edges.The magnitude function is given by

$$m_1(x,y) = (r+\epsilon)^{-\gamma} \qquad (7)$$

$$m_2(x,y) = \exp(-r^2/\sigma^2) \qquad (8)$$

where 'γ' and 'σ' represents positive parameters to control the decrease, 'ε' is a small positive constant to prevent division by zero at the origin.

VFC snakes have larger capture range and less computational time but it has drawback that weak edges might be overwhelmed by the strong edges along with the noise.

3.3.3 Adaptive Diffusion Flow

This novel external force method was introduced by Yuwei Wu et al[17,19] to overcome the difficulties of gradient vector flow. The difficulties faced by gradient vector flow is unable to detect the deep and narrow concavity. So, the adaptive diffusion flow gives the better result as it adopts three things as follows:

1) substituting smoothness term in GVF by hypersurface minimal function so that avoiding weak edge leakages.

2) author made use of the p(x) harmonic maps in which p(x) ranges from 1 to 2, 3 including infinity Laplace functional so that it make sure that it reaches to the deep and narrow concavities.

Replacing smoothening energy term of GVF is replaced by hyper surface harmonic minimal functional helps to preserve weak edges and smooth vector filed. The hypersurface harmonic function is given by equation (9)

$$E(v) = \{\iint \frac{1}{p|\nabla f|}\left(\sqrt{1+|G\sigma\otimes\nabla v|^2}\right)^{p|\nabla f|}\} \quad (9)$$

To reach the deep and narrow cavities, as Laplacian operator comprises of directional derivatives, normal and along the tangent. So, vector fields using infinite energy Laplacian energy function used to minimize Lipschitz extension L^p which is represented by equation (10) when $p\rightarrow\infty$.

$$E_\infty = \int |\nabla G\sigma\otimes\nabla v|_{L^\infty(\Omega)} d\Omega \quad (10)$$

The mathematical model for adaptive diffusion flow is given by equation (11)

$$E(u) = \iint \left[g.\left(-m.|G\sigma\otimes\nabla u|_{L^\infty} + (1-m).\frac{1}{p(|\nabla f|)}.\left(\sqrt{1+|G\sigma\otimes\nabla u|^2}\right)^{p(|\nabla f|)}\right) + h.(|u-f_x|^2)\right] d\Omega \quad (11)$$

where $|G\sigma\otimes\nabla u|^2 = \Theta$ and g, h, mare the weighting functions. This method has advantages like it takes a smaller number of iterations and less computational

So, there are various methods in literature for leaf segmentation[20] but we are using the above three parametric active contour methods.

III. RESULTS AND CONCLUSION

In this section, the various stages of results have been discussed in detail as follows:

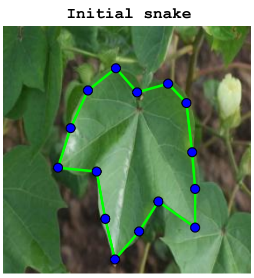
The original image acquired from the field is as shown in figure 2(a) and it is resized into 256x256 as shown in figure 2 (b).

Figure 2(a): Original Image of size 6000x4000

(b)

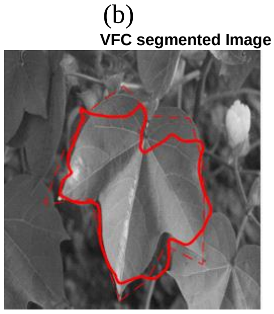
Figure 2(b) Resized Image of size 256x256

The resized image preprocessed using filter inbuilt function of matlab.Then the preprocessed images are applied to three different methods ADF, VFC, and GVF. Figure 3(a) is the initial contour image, figure 3(b) is the preprocessed image and the output of the above methods are shown in figure 3(c), 3(d) and 3(e) respectively.

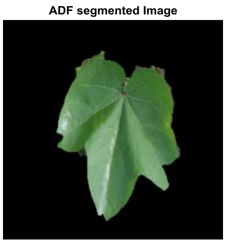


(a)

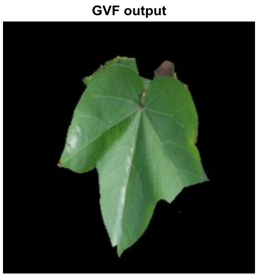
(b)



(c)



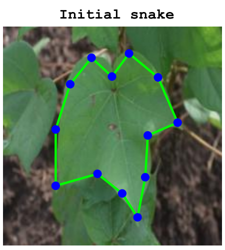
(d)



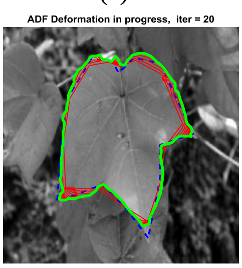
(e)

Figure 3(a) Initial Contour (b) preprocessed image (c) VFC output image (d) ADF output image (e) GVF output image

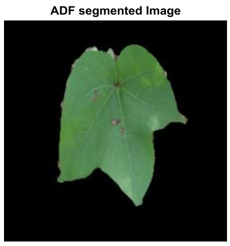
The pre-processed image has been segmented using Gradient Vector Flow (GVF),Vector Field Convolution(VFC) and Adaptive Diffusion Flow(ADF) methods by initializing the curve as shown in figure 4(a). the parameters such as $\alpha = 0.05$; $\beta = 0.5$; $\gamma=1$; k=0.6 are kept constant by varying the number of iterations till the leaf has been segmented with the ADF method. The corresponding evolution process and segmentation results are shown in figures 4(b) and 4(c) respectively. Similarly, using VFC and ADF results are shown in figures 5(a), 5(b) respectively.



(a)



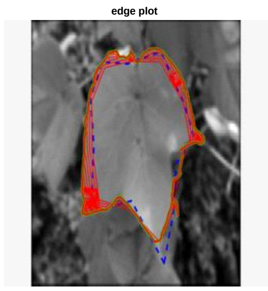
(b)



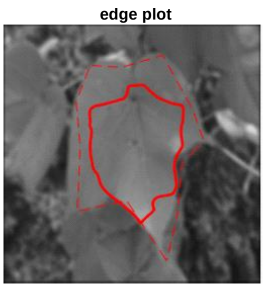
(c)

(d)

Figure 4(a) Initial contour (b) deformation process (c) Segmented image (d) Ground truth image



(a)



(b)

Figure 5(a) ADF deformation image (b) VFC deformation image

The Table 1 gives the details regarding the number of iterations and CPU processing time.

Image	GVF		VFC		ADF	
	No of Iterations	Time in Sec	No of Iterations	Time in Sec	Number of Iterations	Time in Sec
Leaf1	30	13.89	30	14.86	30	9
Leaf2	30	9	20	9.8	20	4.81
Leaf3	30	9.84	20	9.96	20	5.82

Leaf4	40	13.64	20	10.23	20	5.63
Leaf5	30	9.88	20	10.25	20	5.24
Leaf6	40	13.41	20	10.13	20	5.31

The corresponding results such as the number of iterations, time taken for segmentation for the different leaves are tabulated in Table-1. The segmented results are evaluated by the pathological expert and the ground truth images to determine the number of true positive, false positive, true negative and false negative values of segmented images tabulated in Table-2. From these values, the performance parameters such as precision, recall, dice, Manhattan and Jaccard have been computed using equation (12) to equation (16) respectively.

Precision=TP/(TP+FP) (12)

Recall = TP/(TP+FN) (13)

Dice index = 2.0 x(precision x recall)/(precision+recall) (14)

Manhattan index = TP+TN/(TP+FP+TN+FN) (15)

Jaccard index = TP/(TP+FP+FN) (16)

Table 2: Values of True Positive, True Negative, False Positive and False Negative

	TP	FP	FN	TN
GVF	117	36	0	117
VFC	103	50	04	103
ADF	131	22	02	131

Table 3: Precission, recall, Dice, Manhattan, Jaccard index values

	Precision	Recall	Dice	Manhattan	Jaccard
GVF	0.7647	1	0.8666	0.8666	0.7647
VFC	0.6732	0.9626	0.7923	0.8765	0.6560
ADF	0.8562	0.9849	0.9160	0.9160	0.8451

Then, the computed results were tabulated as shown in Table 3. From Table 1, the graph of a number of iterations versus time taken for GVF, VFC and ADF segmentation methods have been drawn as shown in figure 6(a). The diffrent parameter with diffrent segmentation methods are drawn in fig 6(b). From the graphs, it shows that the ADF segmentation methods takes less computational time and better segmentation results as compared to GVF and VFC.

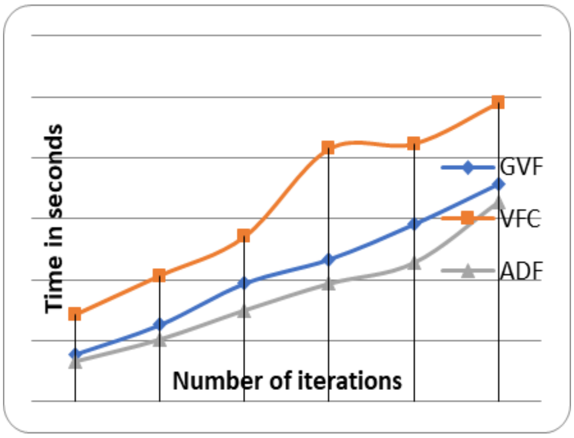


Fig 6(a): Time in seconds versus Number of iterations

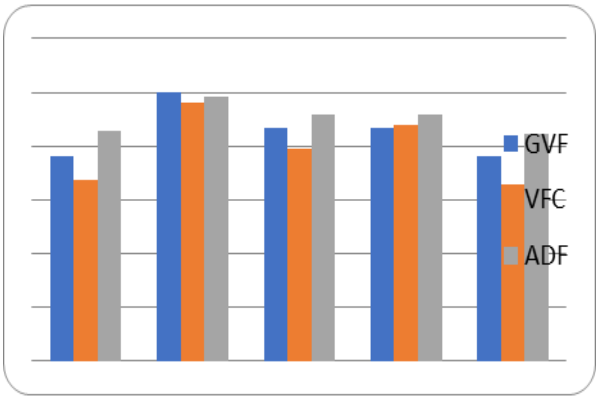


Fig 6(b): Performance parameters of GVF, VFC and ADF

From the figure 6(b) it is observed that the performance parameters like precision, Recall, Dice, Manhattan, Jaccard using GVF method are 0.76, 1, 0.86, 0.86 and 0.76 , using VFC 0.67,0.96,0.79,0.87 and 0.65, using ADF 0.85, 0.98, 0.91, 0.91, 0.84 respectively. From the results, it shows that ADF performance parameters are better than the GVF and VFC methods.

IV. CONCLUSION

This paper gives a study of three different parametric deformable model algorithms. The study of ADF, GVF, VFC algorithms are used for leaf segmentation. Experimental analysis on segmentation of cotton leaf images with natural background showed that ADF is much faster and accurate than the GVF and VFC. It can be seen that the adaptive diffusion flow method is better than the other two methods in terms of computational time, iterations and performance parameters.

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