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Research Article

A Study and Implementation of Active Contour Model For Feature Extraction: With Diseased Cotton Leaf as Example

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Abstract

Feature extraction is a significant constituent of a pattern recognition system. It carries out two assignments: converting input parameter vector into a feature vector and/or reducing its dimensionality. A distinct feature extraction algorithm makes the classification process more effectual and efficient. The allocation and recognition of cotton leaf diseases are of the major importance as they have a cogent and momentous impact on quality and production of cotton. In this work we present a snake based approach for the segmentation of images of diseased cotton leaves. We extract Hu's moments which can be used as shape descriptors for classification. A theory of two-dimensional moment invariants for planar geometric figures is also presented. Three diseases have been considered, namely Bacterial Blight, Myrothecium and Alternaria. The testing samples of the images are gathered from CICR Nagpur, cotton fields in Buldhana and Nagpur district.

Keywords: *Cotton leaf diseases, Active contour model, Spatial moment, Central moments, Snake segmentation.*

1. Introduction

Cotton is an important cash crop in India. Cotton plants suffer from multifarious diseases that can prove detrimental to the quality and quantity of the yield. In Andhra Pradesh state government reported that 20.46 lacs farmers suffered from cotton crop failure in 33.73 lacs acres and lost Rs.3071.6 crores. In Maharashtra the estimated loss is about Rs.10000/- crores in recent years.

Mainly the detection and identification of leaf diseases can be done by naked eye observation (Weizheng S. *et al, 2008*).This in turn requires continuous monitoring which is not viable in large farms. The farmers usually judge the symptom by their experiences. The misidentification leads to some erroneous control measurements such as desultory and untimely use of pesticides

Automatic detection of plant diseases is an essential research topic as it may prove benefits in monitoring and supervising large crop fields and early detection of the symptoms of diseases as soon as they appear on plant leaves (Rampf T.*et al*, 2010; Hillnhuetter C. *et al*, 2008). Such systems include image enhancement, image segmentation, feature extraction and training blocks

2. Cotton leaf Diseases

Leaf spots are regard as the important entity indicating the existence of disease and considered as indicator of crop disease (EI-Helly M.*et al*, 2003). The leaf diseases considered are Bacterial Blight, Myrothecium and Alternaria. The symptoms of these diseases are as:

Bacterial Blight 	The appearance of many minute water soaked angular spots scattered on the ventral surface of leaves, these spots turn brown and then are converted into black dead lesions on both sides of the leaf. Many a time one or more veins in part or whole become water soaked and then turn brown or black, this symptom is called as "Black vein". It may appear independently or together with angular leaf spots.
Myrothecium 	The appearance of circular to semicircular light brown to tan colored spots with violet to reddish brown margins. Later on shield shaped small fruiting bodies are produced in the central portion of the spot. Big shot holes appear in leaves as the center dries and drops off.
Alternaria 	In early stage of infection pale green spots with irregular margins develop on leaves. Later on, these spots enlarge and concentric rings and cracked centre develops. Severe infection causes drying and falling of leaves.

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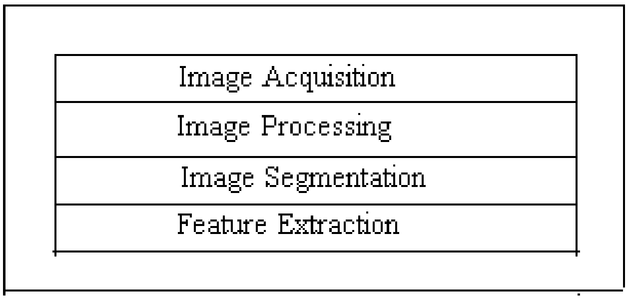
3. The Proposed Approach

The all-embracing concept for any vision related approach for image classification remains the same. Initially the digital images are procured using a digital camera. Then image processing techniques are applied to these images to extract features. The useful features are used to train the network which performs the classification.

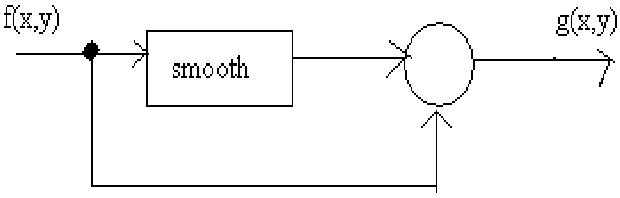


4. Image Acquisition

The images required for the experimentation are acquired by using Cannon A460 digital camera and Leica Wild M3C stereo zoom microscope at CICR Nagpur.

5. Image Enhancement

Low pass filter is used for smoothing the images and noise reduction. It perform averaging of the current pixel with the neighbouring pixel values.Their effect is observed as blurring of the image. The rotationally symmetric gaussian low pass filter is used .



6. Image segmentation

Segmentation involves separating an image into regions corresponding to objects by identifying common properties. In this work we have used active contour model for segmentation.

Active contour model (snake) is a framework for delineating an object outline from a noisy image. Snake is an energy minimizing, deformable spline which is influenced by constraint and image forces that pull it towards object contours.

Active contour models provide a unified solution to several image processing problems. However the energy minimization process is prone to oscillation unless a very small time step is used, with the side-effect that convergence is slow. Also the models only incorporate edge information, ignoring other image characteristics such as texture and color. The snakes must be initialized close to the feature of interest to avoid being distracted by noise and clutter.

Each element of the contour u depends on two parameters, the space parameter that varies between 0 to N–1 and time t. Thus

$$u(s, t) = (x(s, t), y(s, t)) \quad (1)$$

At a given time this function represents a mapping from the parametric domain $s \in [0, N]$ into the image plane R^2.The total energy of the model (E_{snake}) is given by the sum of the energy of each snake elements:

$$E_{snake} = \int_0^{N-1} E_{element}\left(u(s,t)\right)ds \quad (2)$$

The energy of each element consists of three basic energy terms:

$$E_{element} = E_{internal}(u) + E_{external}(u) + E_{image}(u) \quad (3)$$

The internal energy $E_{internal}$ represents the constraints that give the model tension and stiffness. The external energy $E_{external}$ represents external constraints imposed by human operators or automatic initialization procedures. The image energy E_{image} drives the model towards salient features which are generated by processing the image to enhance light and dark lines, edges, or terminations. Each of these energy terms produces a corresponding force that can be used to move the model and hence minimize its energy

Internal Energy

The internal energy of a snake element is defined as:

$$E_{internal}(u) = \alpha(s)\left|\frac{\partial u}{\partial s}\right|^2 + \beta(s)\left|\frac{\partial^2 u}{\partial s^2}\right| \quad (4)$$

This energy consists of a first-order term controlled by $\alpha(s)$, and a second-order term controlled by $\beta(s)$. Minimizing the first-order energy term makes the snake contract by introducing *tension*; minimizing the second-order term makes the snake resist bending by producing *Stiffness.*

In other words, the curve is predisposed to have minimal (preferably zero) velocity and acceleration with respect to the parameter s. The weights $\alpha(s)$ and $\beta(s)$ control the relative importance of the tension and stiffness terms.

External Energy

A spring-like attractive force can be generated between a snake element u and a point i in an image using the following external energy term:

$$E_{external}(u) = k\,|i - u|^2 \quad (5)$$

This energy is zero when u = i, and takes the value of k when i – u = ±1.

Image (Potential) Energy

A potential energy *(P)* generated by processing an image $I(x, y)$ is used to drive snakes towards features of interest. Two potential energy terms described below drive snakes towards lines (regions) and edges; a third term for detecting corners (terminations) was proposed by Kass et al (1987; 1988). The total image energy can be expressed as a weighted combination of these functionals:

$$P(u) = E_{image} = w_{line}E_{line}(u) + w_{edge}E_{edge}(u) + w_{term}E_{term}(u) \quad (6)$$

Thus the image energy is a linear combination of line, edge and termination energy terms which are calculated from the raw image.

*Line (Region) Functional:*The simplest potential energy is the smoothed image intensity:

$$E_{line}(u) = G_{\sigma} * I(u) \quad (7)$$

The Gaussian filter *G* has standard deviation. According to the sign of w_{line} in Equation (6), the snake will be attracted either to light or to dark lines in the image.

Edge Functional: The active contour model is used as semi-global edge-detector that minimizes a potential energy in which minima correspond to strong edges. A snake can be given an affinity for edges using a gradient-based potential energy:

$$E_{edge}(u) = -\left|\frac{\partial}{\partial u} G_{\sigma} * I(u)\right|^2 \quad (8)$$

There are some limitations of edge-based energy terms. The models often fail to lock on to weak edges or become distracted from the feature of interest by stronger but less interesting edges. The step by step procedure used for implementing the snake is as follows:

1) Firstly the diseased leaf image is selected and then the value of σ for Gaussian smoothing is selected.

2) The initial position of the snake is selected by clicking on the image and selecting the control points which are later interpolated into a contour.

3) Specify the following control parameters for the snake:

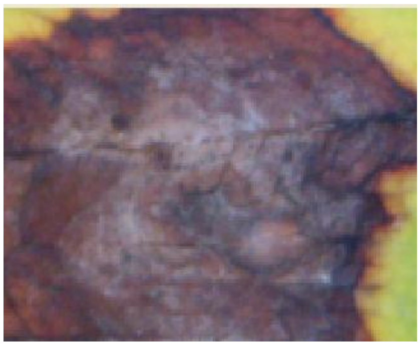
α (alpha):It specify the elasticity of the snake.
β (beta): It specify the rigidity of the snake.
γ (gamma): It specify the step size of the snake.
$W(E_{line})$:It is the weighing factor for intensity based potential term.
$W(E_{edge})$:It is the weighing factor for edge based potential term.
$W(E_{term})$:It is the weighing factor for termination potential term.

4) Specify the number of iterations for which contour position is calculated.

Original Image

Snake Evolvement

Snake Evolvement



Processed Image

7. Feature extraction

The spatial moments of the gray value-function $f(x; y)$ of an object is given by

$$m_{p,q} = \iint x^p\, y^q f(x,y)dxdy \tag{9}$$

The integration is calculated over the area of the object. For binary images the gray value function $f(x;\, y)$ is

$$f(x,y) = b(x,y) = \begin{cases}1\\0\end{cases} \tag{10}$$

and can be neglected in the formulas. In the Eq.(10) b(x,y) equals to 1 for object and o for background. The order of a moment depends on the indices p and q of the moment $m_{p,q}$. The sum $p + q$ of the indices is the order of the moment $m_{p,q}$.
For zero order moment $((p;\, q) = (0;\, 0))$ and describes the area A of the object.

$$m_{o,o} = \iint dxdyb(x,y) \tag{11}$$

For first order moments $((p;\, q) = (1;\, 0)$ or $(0;\, 1))$ and gives information about center of gravity of the object.

$$m_{1,0} = \iint dxdyx\, f(x,y) \tag{12}$$

$$m_{0,1} = \iint dxdyy\, f(x,y) \tag{13}$$

The center of gravity of the object is calculated as

$$x_c = \frac{m_{1,0}}{m_{0,0}}$$

$$y_c = \frac{m_{0,1}}{m_{0,0}}$$

The second order moments are given by $((p;\, q) = (2;\, 0)$ or $(0;\, 2)$ or $(1;\, 1))$.

$$m_{2,0} = \iint dxdyx^2\, f(x,y) \tag{14}$$

$$m_{0,2} = \iint dxdyy^2\, f(x,y) \tag{15}$$

$$m_{1,1} = \iint dxdyxy\, f(x,y) \tag{16}$$

The *central moments* can be obtained by reducing the spatial moments with the center of gravity $(x_c;\, y_c)$ of the object.The central moments are calculated as follows:

$$\mu_{p,q} = \iint (x - x_c)^p\, (y - y_c)^q\, f(x,y)dxdy \tag{17}$$

From this the following moments can be calculated

$$\mu_{0,0} = m_{0,0}$$
$$\mu_{1,0} = \mu_{0,1} = 0$$

The central moments of first or higher order can be derived from the spatial moments as the central moments of first and second order can be derived from spatial moments using above equation as follows:

$$\mu_{p,q} = \frac{m_{p,q}}{m_{0,0}} - \left(\frac{m_{1,0}}{m_{0,0}}\right)^p * \left(\frac{m_{0,1}}{m_{0,0}}\right)^q \tag{18}$$

$$\mu_{1,0} = \frac{m_{1,0}}{m_{0,0}} - \left(\frac{m_{1,0}}{m_{0,0}}\right) = 0 \tag{19}$$

$$\mu_{0,1} = \frac{m_{0,1}}{m_{0,0}} - \left(\frac{m_{0,1}}{m_{0,0}}\right) = 0 \tag{20}$$

$$\mu_{2,0} = \frac{m_{2,0}}{m_{0,0}} - \left(\frac{m_{1,0}}{m_{0,0}}\right)^2 = \frac{m_{2,0}}{m_{0,0}} - x^2{}_c \tag{21}$$

$$\mu_{0,2} = \frac{m_{0,2}}{m_{0,0}} - \left(\frac{m_{0,1}}{m_{0,0}}\right)^2 = \frac{m_{0,2}}{m_{0,0}} - y^2{}_c \tag{22}$$

$$\mu_{1,1} = \frac{m_{1,1}}{m_{0,0}} - \left(\frac{m_{1,0}}{m_{0,0}}\right) * \left(\frac{m_{0,1}}{m_{0,0}}\right) = \frac{m_{1,1}}{m_{0,0}} - x_c * y_c \tag{23}$$

where $x_c;\, y_c$is the center of gravity of the object. The central moments are invariant to translations of the object therefore they are used to describe the form of the object. The central moments are made invariant to size of the object by using them in the normalised form. Dividing the central moments $\mu_{p,q}$ with powers of A we get *central normalized moments* $V_{p,q}$.

$$v_{p,q} = \frac{\mu_{p,q}}{m_{0,0}^{\frac{p+q}{2}+1}} \tag{24}$$

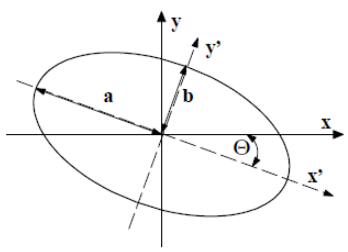
The main advantage of normalized moments is that they are invariant to the size of the object. The central moments of second order $\mu_{2,0}$,$\mu_{0,2}$ and $\mu_{1,1}$contain terms, in which the gray value function $f(x;\, y)$, of the object is multiplied with the square of the distance from the center of gravity $(x_c;\, y_c)$. The inertial tensor of rotation of the object about its center of gravity can be calculated using the three central moments of second order as follows:

$$J = \begin{bmatrix}\mu_{2,0} & -\mu_{1,1}\\ -\mu_{1,1} & \mu_{0,2}\end{bmatrix} \tag{25}$$

Using the inertial tensor several parameters can be calculated. The main inertial axis is obtained by calculating the eigenvalues of the inertial tensor:

$$\lambda_{1,2} = \sqrt{\frac{1}{2} * \left(\mu_{2,0} + \mu_{0,2}\right) \pm \sqrt{4 * \mu_{1,1}^2 - (\mu_{2,0} - \mu_{0,2})^2}} \tag{26}$$

The main inertial axes of the object keep up a correspondence to the semi-major and semi-minor axes a and b of the image ellipse which is used for the approximation of the object.The main inertial axes are those axes, around which the object can be rotated with minimal (major semi-axis a) or maximal (minor semi-axis b) inertia.



The tilt angle between the x-axes and the axis, about which the object is rotated with minimal inertia (i.e. the direction of the major semi-axis a) give the orientation of the object.This corresponds to the eigenvector with minimal eigenvalue.It is calculated as follows:

$$\theta = \frac{1}{2}\ arctan\ \frac{2\mu_{1,1}}{\mu_{2,0}-\mu_{0,2}} \tag{27}$$

The form of the object can be described by using the parameters such as roundness and eccentricity.The roundness k and eccentricity ε can be calculated by dividing the square of the perimeter *p* with the area *A*.

$$k = \frac{p^2}{A} \tag{28}$$

The eccentricity ε is calculated as

$$\epsilon = \frac{\sqrt{a^2-b^2}}{a} \tag{29}$$

Where a and b are semi-major and semi-minor axes of the object.*Eccentricity* can be calculated from the central moments of second order as

$$\epsilon = \frac{(\mu_{2,0}-\mu_{0,2})^2-4\mu_{1,1}^2}{(\mu_{2,0}+\mu_{0,2})^2} \tag{30}$$

Hu introduced seven nonlinear functions which are invariants under object's translation, scale and rotation. The set of seven third order boundary central moments are given by the following equations

$$M1 = \eta_{20} + \eta_{02} \tag{31}$$

$$M2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}{}^2 \tag{32}$$

$$M3 = (\eta_{30} - \eta_{12})^2 + (3\eta_{21} - \eta_{03})^2 \tag{33}$$

$$M4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2 \tag{34}$$

$$M5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] +3(\eta_{21} - \eta_{03}) \tag{35}$$

$$M6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] +4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}) \tag{36}$$

$$M7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] +(3\eta_{12} - \eta_{30})(\eta_{21} + \eta_{03})\left[3(\eta_{30} + \eta_{12})^2 - (\eta 21 - \eta 03)^2\right] \tag{37}$$

8. Result

The table 1 shows the moments derived from each type of cotton leaf disease under consideration. The set of seven moments are treated as seven feature vectors which can be used for classification.

Table 1: Moments for cotton leaf diseases

Bacterial Blight	Myrothecium	Alternaria
1.6202e-006	0.012999	0.0010557
1.6076e-006	0.010117	0.00087101
0.0012012	0.12691	0.034868
0.0012139	0.1207	0.033656
1	1	1
0.0012712	0.099054	0.028825
0.99976	0.99215	0.95599

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