Early Pest Identification in Greenhouse Crops using Image Processing Techniques

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Abstract

Early disease detection is a major challenge in agriculture field. Hence proper measures has to be taken to fight bioagressors of crops while minimizing the use of pesticides. The techniques of machine vision are extensively applied to agricultural science, and it has great perspective especially in the plant protection field,which ultimately leads to crops management. Our goal is early detection of bioagressors. The paper describes a software prototype system for pest detection on the infected images of different leaves. Images of the infected leaf are captured by digital camera and processed using image growing, image segmentation techniques to detect infected parts of the particular plants. Then the detected part is been processed for futher feature extraction which gives general idea about pests. This proposes automatic detection and calculating area of infection on leaves of a whitefly (*Trialeurodes vaporariorum* Westwood) at a mature stage.

Keywords: *Greenhouse crops, early pest detection, Machine vision, image processing, feature extraction*

1. Introduction

A lot of research has been done on greenhouse agrosystems and more generally on protected crops to control pests and diseases by biological means instead of pesticides. Research in agriculture is aimed towards increase of productivity and food quality at reduced expenditure and with increased profit, which has received importance in recent time. A strong demand now exists in many countries for non-chemical control methods for pests or diseases. Greenhouses are considered as biophysical systems with inputs, outputs and control process loops. Most of these control loops are automatized (e.g., climate and fertirrigation control). However no automatic methods are available which precisely and periodically detect

the pests on plants. In fact, in production conditions, greenhouse staff periodically observes plants and search for pests. This manual method is to time consuming.

Diagnosis is a most difficult task to perform manually as it is a function of a number of parameters such as environment, nutrient, organism etc. With the recent advancement in image processing and pattern recognition techniques, it is possible to develop an autonomous system for disease classification of crops. [2]

In this paper, we focus on early pest detection. First, this implies to regularly observe the plants. Disease images are acquired using cameras or scanners. Then the acquired image has to be processed to interpret the image contents by image processing methods. The focus of this paper is on the interpretation of image for pest detection.

1.1 Need of early detection of pests:

Early detection of pest or the initial presence of a bioagressor is a key-point for crop managemant. The detection of biological objects as small as such insects (dimensions are about 2mm) is a real challenge, especially when considering greenhouses dimensions (10–100m long). For this purpose different measures are undertaken such as manual observation of plants. This method does not give accurate measures. Hence automatic detection is very much important for early detection of pests.

1.2 Application of computer vision:

Our objective is to develop a detection system that is robust and easy to adapt to different applications. Traditional manual counting is tedious, time consuming and subjective, for it depends on observer's skill. To overcome these difficulties, we propose to automate identification and counting, based on computer vision

Computer vision methods are easier to apply in our system we simply use a consumer electronics scanner to get high-resolution images of leaves. Computer vision has a wider field of application such as disease and pest control. It has been applied in respectively, to quantify symptoms various pests attacks, or in to develop an automated plant monitoring system in greenhouses.

1.3 Image acquisition

Fig. 1

For this study, whitefly *Trialeurodes Vaporariorum* was chosen because this bioagressor requires early detection and treatment to prevent durable infection. Eggs and larvae identification and counting by vision techniques are difficult because of critical dimension (eggs) and weak contrast between object and image background (larvae). For these reasons we decided to focus first on adults. Since adults may fly away, we chose to scan the leaves when flies were not very active. Samples were manually cut and scanned directly in the greenhouse as shown in Fig.1.

Once the image is acquired and scanned the next step is to implement image processing technique in order to get the information about pest.

2. Image processing operation

In electrical engineering and computer science, image processing is any form of signal processing for which the input is an image, such as a photograph or video frame. The output of image processing may be either an image or, a set of characteristics or parameters related to the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal-processing techniques to it.

In any image processing application the important input is IMAGE. An image is an array, or a matrix, of square pixels (picture elements) arranged in columns and rows. An image may be defined as a two-dimensional function, f(x,y), where x and y are spatial coordinates, and the amplitude of f at any pair of coordinates (x,y) is called the intensity or gray level of the image at that point. When x, y, and the amplitude values of f are all finite, discrete quantities, we call the image a digital image. [4]

For the purpose of automatic detection of pests on scanned leaves the algorithm has to be followed. This algorithm is shown in fig.2. It is executed as follows.

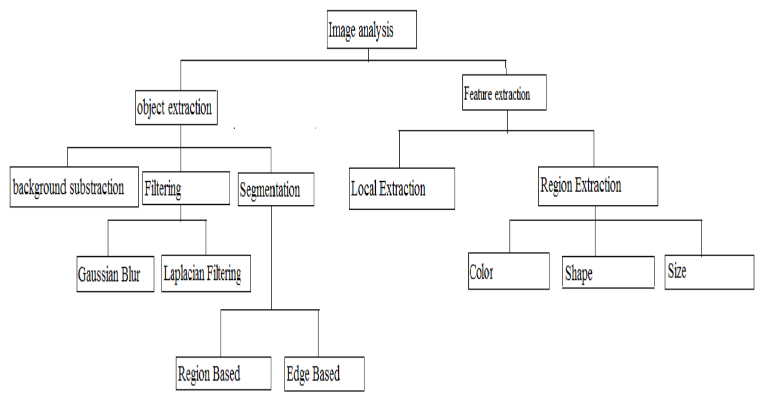

Fig. 2

Object extraction is followed by *feature extraction. Object extraction* itself decomposes into a sequence (*background substraction*, then *filtering*, and finally *segmentation*). Since *background substraction* appears on the top and corresponds to a concrete program to execute, the system invokes it. This program automatically extracts a leaf from its background image (Fig.3(a)). The second sub-operator, *filtering* may be performed in two different ways (Gaussian or Laplacian filtering). It runs the corresponding denoising program and the result is presented in (Fig.3(b)).The next operator, *segmentation*, also corresponds to a choice between two alternative sub-operators: *region-based* and *edge-based*. The result after segmentation is shown in (Fig.3(c)).

Similarly, once the objects extracted, the second step of *image analysis*, feature extraction, computes the attributes corresponding to each region, according to the domain feature concepts (e.g., color, shape and size descriptors) and to the operator graph. The process runs up to the last programming the decomposition (in the example, it appears to be *shape feature extraction*). Finally, through this we get the information about pests and its features which is useful data for the preventive measures that has to be undertaken. [3]

3.Object Extraction

3.1. Background Substraction:

Background subtraction is a commonly used class of techniques for segmenting out objects of interest in a IMAGE. The name subtraction comes from the simple technique of subtracting the observed image from the estimated image and thresholding the result to generate the objects of interest.

In many vision applications, it is useful to be able to separate out the regions of the image corresponding to objects in which we are interested, from the regions of the image that correspond to background. Thresholding often provides an easy and convenient way to perform this segmentation on the basis of the different intensities or colors in the foreground and background regions of an image. Thresholding is used to change pixel values above or below a certain intensity value (threshold). [4]

For an image f(x,y) any point(x,y) for which:

$$f(x; y) > T \quad (1)$$

is called an object point, otherwise it is background point.

A threshold image g(x,y) is defined as:

$$g(x; y) = 1 \text{ if } f(x; y) > T \quad (2)$$
$$\text{and } g(x; y) = 0 \text{ if } f(x; y) \leq T. \quad (3)$$

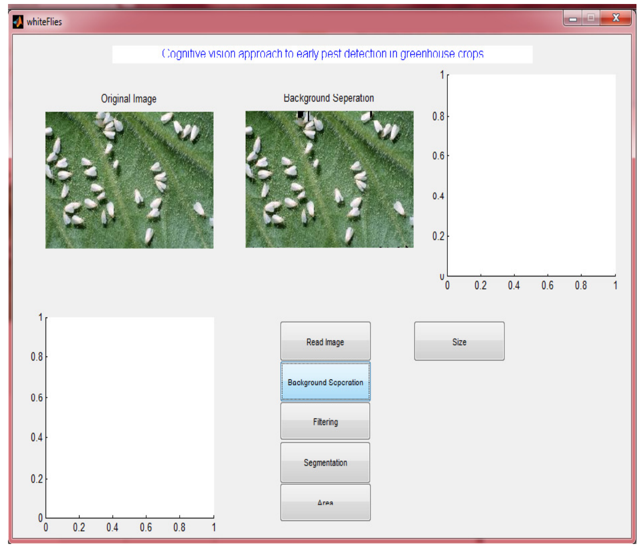

Fig. 3 (a) Result after background substraction operation

3.2 Filtering:

Filtering means to filter an image. A filter is defined by a kernel, which is a small array applied to each pixel and its neighbors within an image. The process used to apply filters to an image is known as convolution.

An image has to be filter for smoothing, sharpening, removing noise, edge detection. The filtering process of an digital image is carried out in spatial domain. In linear spatial filtering the response of a filtering is given by sum of products of filtering coefficient and the corresponding image pixels. [4]

In general linear filtering of an image of size MN with a filter mask of size mn is given by:

$$g(x,y) = \frac{\sum_{s=-a}^{s=a} \sum_{t=-b}^{t=b} w(s,t) f(x+s, y+t)}{\sum_{s=-a}^{s=a} \sum_{t=-b}^{t=b} w(s,t)} \quad (4)$$

Here Gaussian type of filtering is used.

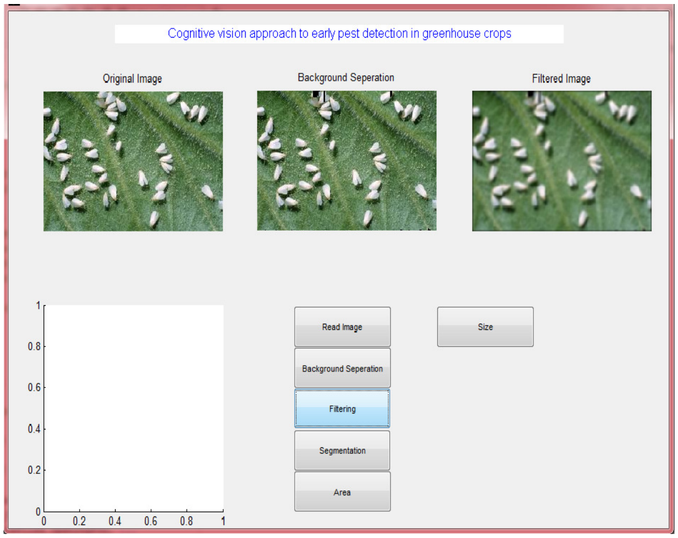

Fig. 3 (b) Result after filtering operation.

3.3 Segmentation:

Segmentation is one of the first steps in image analysis. It refers to the process of partitioning a digital image into multiple regions (sets of pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images.

Here EDGE DECTION type of segmentation is used.

Edge detection is a fundamental tool in image processing and computer vision, particularly in the areas of feature detection and feature extraction, which aim at identifying points in a digital image at which the image brightness changes sharply or, more formally, has discontinuities. An edge is the boundary between an object and the background, and indicates the boundary between overlapping objects. This means that if the edges in an image can be identified accurately, all of the objects can be located and basic properties such as area, perimeter, and shape can be measured. Edge detection refers to the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions.

Edges can be detected with the help of gradient/derivative type operators. Gradient images are created from the original image for this purpose. Each pixel of a gradient image measures the change in intensity of that same point in the original image, in a given direction. To get the full range of direction, gradient images in the x and y directions are computed. After gradient images have been computed, pixels with large gradient values become possible edge pixels. The pixels with the largest gradient values in the direction of the gradient become edge pixels, and edges may be traced in the direction perpendicular to the gradient direction.

The Gradient of an image f(x,y) at location (x,y)

$$\nabla f = \begin{bmatrix} G_x \\ G_y \end{bmatrix} = \begin{bmatrix} \delta f / \delta x \\ \delta f / \delta y \end{bmatrix} \qquad (5)$$

For these particular type of edge detection SOBEL OPERATOR is been used.

The Sobel operator is used in image processing, particularly within edge detection algorithms. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. Technically, it is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function.

The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. If we denote A as the source image, and Gx and Gy are two images which at each point contain the horizontal and vertical derivative approximations, [4] the computations are as follows:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} * \mathbf{A} \text{ and } G_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} * \mathbf{A} \qquad (6)$$

3.4. Calculation of infected area:

By using image analysis we can calculate the percentage of infected area. The given output is in form of pixels. So the infected area in percentage can be calculated by simple formula:

Percent infection= (Infected area ÷ total area) × 100

From this results we can calculate the total infection on leaf which in turn gives us information about intensity of pests infection on leaf.

3.5. Calculation of size of each pest:

Calculation of size of each pest is also done. This gives us idea about the growth of pests and also its life stage whether it is mature stage or is in pre mature stage. The given output is in form of pixels .

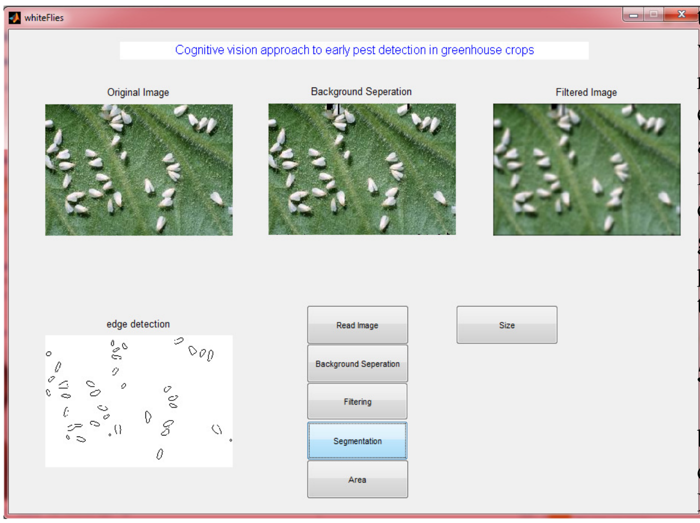

Fig. 3 (c) Result after segmentation operation

3.6 Table (Results):

No. of pests		1	2	3	4	5	6	7	8	9	10	11	12
Size	Width	9	8	14	14	7	21	12	11	14	14	9	8
	Height	8	14	10	16	13	9	7	7	8	7	8	10
Area of infection of each pest		21	30	37	29	27	45	27	25	31	30	23	32

4 .Conclusion:

Our first objective is to detect other whitefly stages (eggs, larvae) and other bioagressors (aphids) or plant diseases (powdery mildew). Thanks to our cognitive approach, it is simple to introduce new objects to detect or new image processing programs to extract the corresponding information. We propose an original approach for early detection of bioagressors, which has been applied to detect mature whiteflies on rose leaves. To detect biological objects on a complex background, we combined scanner image acquisition, sampling optimization, and advanced cognitive vision. It illustrates the collaboration of complementary disciplines and techniques, which led to an automated, robust and versatile system. The prototype system proved reliable for rapid detection of whiteflies. It is rather simple to use and exhibits the same performance level as a classical manual approach. Moreover, it detects whiteflies three times faster and it covers three times more leaf surface. The context of our work is to automate operations in greenhouses. Our goal is rather to better spot the starting points of bioagressors attacks and to count these latter so that necessary action can be taken.

5. Future Work:

The results presented in this paper are promising but several improvements in both material and methods can be carried out to reach the requirements of an Integrated Pest Management system. In future the feature extraction of image will be carried out. From this results type, shape, color, texture of pest will be detected. From all this measures what preventive action against pest should be taken will be decided through which the production of crops can be increased.

6. References:

1]Martin,V.Thonnat,."A Learning Approach For Adaptive Image Segmentation." In Proceedings of IEEE Trans.Computers and Electronics in Agriculture.2008

2]B.Cunha."Application of Image Processing in Characterisation of Plants." IEEE Conference on Industrial Electronics.2003.

3]Santanu Phadikar, Jaya Sil."Rice Disease Identification Using Pattern Recognition Techniques." IEEE 10th International Conference On I.T.E.2007.

4]Rafael C. Gonzalez, Richard E. Woods. "Digital Image Processing'',2nd edition, Pearson education (singapore) pte.ltd.2003.

5]T.F.Burks, S.A.Shearer and F.A. Payne, "Classification of weed species using color texture features and discriminant analysis," Trans. ASAE, vol.43, no.2, pp.441–448, Apr. 2000.

6]R.Pydipati, T.F. Burks and W.S. Lee, "Identification of citrus disease using color texture features and discriminant analysis," Comput. Electron. Agric., vol.52, no.1, pp.49-59, June 2006.

7]T. Kobayashi, E. kanda, K. Kitada, K. Ishigurd and Y. "Detection of rice panicle blast with multisprectural radiometer and the potential use of multisprectural scanner.' Torigoe-2000

8]Laaksonen, J.Koskela, M.Oja, E. , "Self-organizing maps for content-based image retrieval," International Joint Conference on Neural Networks, vol.4, pp.2470-2473 ,1999.

9]R.M. Haralick, K. Shanmugam and I.Dinstein, "Textual features for image classification," IEEE Trans. Syst. Man Cybern., vol.3, no.6, pp. 610–621, Nov. 1973

10]H. Ritter and T.Kohonen. "Self-organizing semantic maps", *Biological Cybernetics*, vol.61, pp.241-254, 1989.

11]P.Sanyal, U.Bhattacharya and S.K. Bandyopadhyay. "Color Texture Analysis of Rice Leaves Diagnosing Deficiency in the Balance of Mineral Levels Towards Improvement of Crop Productivity," 2007 IEEE 10th International Conference on Information Technology, pp. 85-90, 2007 Z. Qin,