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A Study of Image Processing in Agriculture

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ABSTRACT

Agriculture is the backbone of human sustenance on this world. Now a days with growing population we need the productivity of the agriculture to be increased a lot to meet the demands. In olden days they used natural methods to increase the productivity, such as using the cow dung as a fertilizer in the fields. That resulted increase in the productivity enough to meet the requirements of the population. But later people started thinking of earning more profits by getting more outcome. So, there came a revolution called "Green Revolution". In this paper we implemented image processing using MATLAB to detect the weed areas in an image we took from the fields.

Keywords: Image Processing, Agriculture, Image segmentation, classification, Plant diseases.

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I. Introduction:

Control of plant diseases is crucial to the reliable production of food, and it provides significant reductions in agricultural use of land, water, fuel and other inputs. Plants in both natural and cultivated populations carry inherent disease resistance, but there are numerous examples of devastating plant disease impacts as well as recurrent severe plant diseases. However, disease control is reasonably successful for most crops. Disease control is achieved by use of plants that have been bred for good resistance to many diseases, and by plant cultivation approaches such as use of pathogen-free seed, appropriate planting date and plant density, control of field moisture, and pesticide use. Across large regions and many crop species, it is estimated that diseases typically reduce plant yields by 10% every year in more developed settings, but yield loss to diseases often exceeds 20% in less developed settings. Continuing advances in the science of plant pathology are needed to improve disease control, and to keep up with changes in disease pressure caused by the ongoing evolution and movement of plant pathogens and by changes in agricultural practices.
The image processing can be used in agricultural applications for following purposes:

1. To detect diseased leaf, stem, fruit
2. To quantify affected area by disease.
3. To find shape of affected area.
4. To determine color of affected area
5. To determine size & shape of fruits.

1.1 Image Acquisition

The data collection is the major aspect of the data collection in area. The same collection has been used in other studies of automatic scan images segmentation. Various image databases' available world-wide along their name, description and applications. The image acquisition is required to collect the actual source image. An image must be converted to numerical form before processing. This conversion process is called digitization.

1.2 Image Preprocessing

The principle objective of the image enhancement is to process an image for a specific task so that the processed image is better viewed than the original image. Image enhancement methods basically fall into two domains, spatial and frequency domain.

- Spatial domain: as the name suggests in this approach different methods are used, which will affect the manipulation of pixel values of an image
- Frequency domain: in this method first a Fourier transform of the image is computed and then different operations are performed on them and finally results are obtained by getting the inverse Fourier transform of the image.

1.3 Image Segmentation

In image processing, segmentation falls in to the category of extracting different image attributes of an original image. Segmentation subdivides an image into constituent regions or objects. The level to which that subdivision carried out is a problem specific. The simplest method among all segmentation methods is threshold-based method, whose volume uses either a manually or automated generated threshold values for segmentation. In this method first the histogram of the image is computed then a particular value of threshold (intensity) is selected to segment the region. However in this method the intensity values often suffer from non-uniformly distributed contrast values inside the vessels. So, in case of small structure vessel segmentation, global threshold based methods are not useful.

1.4 Image Representation and Description

Representation and description almost always follow the output of a segmentation stage. The first decision must be made whether the data should be represented as a boundary or complete region. Boundary representation is appropriate when the focus is on external shape characteristics whereas regional representation is focusing on internal properties, such as texture and skeletal shape. In plant species identification using digital morphometrics, image representation is done by using leaf shape analysis. The [9] have made a review of previous methods used to analyze the leaf shape using three ways: two-dimensional outline shape of leaf petal, the structure of the vein

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network and the characters of leaf margin. The two-dimensional outline shape of leaf petal is a boundary representation while the structure of the vein network and the characters of leaf margin are regional representation.

1.5 Image Recognition

Recognition is the process that assigns a label to an object based on information provided by its descriptors. Classification is a usual process used to recognize image. Classification is needed to distinguish a plant species with other species based on the data obtained from feature selection. The descriptors from the image data stored in database are compared with the descriptors from the query image. The closer gap within those descriptors is then chosen to appoint the query image to be in which class. Artificial neural network (ANN) and fuzzy logic are the most commonly techniques used in classification.

The purpose of image processing is divided into 5 groups. They are:

1. Visualization - Observe the objects that are not visible.
2. Image sharpening and restoration - To create a better image.
3. Image retrieval - Seek for the image of interest.
4. Measurement of pattern – Measures various objects in an image.
5. Image Recognition – Distinguish the objects in an image.

II. Literacy Review

Various image classification approaches are defined briefly:

1. *On The Basis Of Characteristic Used:*

a. Shape based: This methods make use of the objects' 2D spatial information. Common features used in shape-based classification schemes are the points (centroid, set of points),primitive geometric shapes(rectangle or ellipse), skeleton, silhouette and contour
b. Motion-based: This methods use temporal tracked features of objects for the classification

2. *On The Basis Of Training Sample Used:*

a. Supervised Classification: The process of using samples of known informational classes (training sets) to classify pixels of unknown identity. Example: minimum distance to means algorithm, parallelepiped algorithm, maximum likelihood algorithm
b. Unsupervised Classification: In this type of classification is a method which examines a large number of unknown pixels and divides it into number of classes based on natural groupings present in the image values. Computer determines spectrally separable class and then defines their information value. No extensive prior knowledge is required. Example: K means clustering algorithm.

3. *On The Basis Of Assumption Of Parameter on Data:*

a. Parametric classifier: The parameters like mean vector and covariance matrix are used. There is an assumption of Gaussian distribution. The parameters like mean vector and covariance matrix are frequently generated from training sample .Example: Maximum likelihood, linear discriminant analysis.
b. Non Parametric classifier: There is no assumption about the data. Non-parametric classifiers do not make use of statistical parameters to calculate class separation. Example: Artificial neural network, support vector machine, decision tree classifier, expert system.

4. *On The Basis Of Pixel Information Used:*

a. Per pixel classifier: Conventional classifier generates a signature by using the combination of the spectra of all training-set pixels from a given feature. The contributions of all materials present in the training-set pixels are present in the resulting signature. It can be parametric or nonparametric the accuracy may not meet up because of the impact of the mixed pixel problem. Example: maximum likelihood, ANN, support vector machine and minimum distance.
b. Sub pixel classifiers: The spectral value of each pixel is assumed to be a linear or non-linear combination of defined pure materials called end members, providing proportional membership of each pixel to each end member. Sub pixel classifier has the capability to handle the mixed pixel problem, suitable for medium and coarse spatial resolution images. Example: spectral mixture analysis, sub pixel classifier, Fuzzy-set classifiers.
c. Per-field classifier: The per-field classifier is intended to handle the problem of environmental heterogeneity, and also improves the classification accuracy. Generally used by GIS-based classification approaches.
d. Object-oriented classifiers: Pixels of the image are united into objects and then classification is performed on the basis of objects. It involves 2 stages: image segmentation and image classification Image segmentation unites pixels into objects, and a classification is then implemented on the basis of objects. Example: e Cognition.

5. *On The Basis Of Number Of Outputs For Each Spatial Element:*

a. Hard Classification: Also known as crisp classification in this each pixel is required or forced to show membership to a single class.eg maximum likelihood, minimum distance, artificial neural network, decision tree, and support vector machine.
b. Soft classification: also known as fuzzy classification in this each pixel may exhibit numerous and partial class membership. Produces more accurate result.

III. Image Classification Technique

Difference Techniques for Classification

Classification

The classification methods can be seen as extensions of the detection methods, but instead of trying to detect only one specific disease amidst different conditions and symptoms, these ones try to identify and label whichever pathology that is affecting the plant. As in the case of quantification, classification methods almost always include a segmentation step, which is normally followed by the extraction of a number of features that will feed some kind of classifier. The methods presented in the following are grouped according to the kind of classification strategy employed.

Neural networks

A very early attempt to monitor plant health was carried out by Hetzroni et al. [1]. Their system tried to identify iron, zinc and nitrogen deficiencies by monitoring lettuce leaves. The capture of the images was done by an analog video camera, and only afterwards the images would be digitized. The first step of the proposed algorithm is the segmentation of the images into leaf and background. In the following a number of size and color features are extracted from both the RGB and HSI representations of the image. Those parameters are finally fed to neural networks and statistical classifiers, which are used to determine the plant condition. Artificial Neural networks used to segment the images[13].

Pydipati et al. [2] compared two different approaches to detect and classify three types of citrus diseases. The authors collected 39 texture features, and created four different subsets of those features to be used in two different classification approaches. The first approach was based on a Mahalanobis minimum distance classifier, using the nearest neighbor principle. The second approach used radial basis functions (RBF) neural network classifiers trained with the backpropagation algorithm. According to the authors, both classification approaches performed equally well when using the best of the four subsets, which contained ten hue and saturation texture features.

Huang [3] proposed a method to detect and classify three different types of diseases that affect Phalaenopsis orchid seedlings. The segmentation procedure adopted by the author is significantly more sophisticated than those found in other papers, and is composed by four steps: removal of the plant vessel using a Bayes classifier, equalization of the image using an exponential transform, a rough estimation for the location of the diseased region, and equalization of the sub-image centered at that rough location. A number of color and texture features are then extracted from the gray level co-occurrence matrix. Modified Bee Colony optimization for the selection of different combinations of food sources P.Saravanamoorthi [12] Finally, those features are submitted to an MLP artificial neural network with one hidden layer, which performs the final classification.

Sanyal et al. [14] tackled the problem of detecting and classifying six types of mineral deficiencies in rice crops. First, the algorithm extracts a number of texture and color features. Each kind of feature (texture and color) is submitted to its own specific MLP neural network. Both networks have one hidden layer, but the number of neurons in the hidden layer is different (40 for texture and 70 for color). The results returned by both networks are then combined, yielding the final classification. A very similar approach is used by the same authors in another paper, but in this case the objective is to identify two kinds of diseases (blast and brown spots) that affect rice crops.

The method proposed by AI tries to identify five different plant diseases. The authors did not specify the species of plants used in the tests, and the images were captured *in situ*. After a preprocessing stage to clean up the image, a K-means clustering algorithm is applied in order to divide the image into four clusters. According to the authors, at least one of the clusters must correspond to one of the diseases. After that, for each cluster a number of color and texture features are extracted by means of the so-called Color Co-Occurrence Method, which operates with images in the HSI format. Those features are fed to a MLP Neural Network with ten hidden layers, which performs the final classification.

Kai et al. [15]proposed a method to identify three types of diseases in maize leaves. First, the images are converted to the YCbCr color representation. Apparently, some rules are applied during the thresholding in order to properly segment the diseased regions. However, due to a lack of clarity, it is not possible to infer exactly how this is done. The authors then extract a number of texture features from the gray level co-occurrence matrix. Finally, the features are submitted to an MLP neural network with one hidden layer.

Kai [15] proposed a method to discriminate between pairs of diseases in wheat and grapevines. The images are segmented by a K-means algorithm, and then 50 color, shape and texture features are extracted. For the purpose of classification, the authors tested four different kinds of neural networks: Multilayer Perceptron, Radial Basis Function, Generalized Regression, and Probabilistic. The authors reported good results for all kinds of neural networks.

Support vector machines

SVM proposed a method to identify and classify diseases that affect grapevines. The method uses several color representations (HSI, L*a*b*, UVL and YCbCr) throughout its execution. The separation between leaves and background is performed by an MLP neural network, which is coupled with a color library built a priori by means of an unsupervised self organizing map (SOM). The colors present on the leaves are then clustered by means of an unsupervised and untrained self-organizing map. A genetic algorithm determines the number of clusters to be adopted in each case. Diseased and healthy regions are then separated by a Support Vector Machine (SVM). After some additional manipulations, the segmented image is submitted to a multiclass SVM, which performs the classification into either scab, rust, or no disease.

Here proposed a method to identify two diseases that can manifest in cucumber leaves. The segmentation into healthy and diseased regions is achieved using a statistic pattern recognition approach. In the following, some color, shape and texture features are extracted. Those features

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feed an SVM, which performs the final classification. The authors stated that the results provided by the SVM are far better than those achieved using neural networks.

The system proposed aimed to identify and classify three types of diseases that affect rice crops. The algorithm first applies a particular color transformation to the original RGB image, resulting in two channels (y 1 and y 2). Then, the image is segmented by Otsu's method, after which the diseased regions are isolated. Color, shape and texture features are extracted, the latter one from the HSV color space. Finally, the features are submitted to a Support Vector Machine, which performs the final classification.

The method proposed tries to identify three different kinds of diseases that affect cotton plants. The authors used images not only of leaves, but also of fruits and stems. The segmentation of the image is performed using a technique developed, which was described earlier in this paper (Section 'Thresholding'). After that, a number of features is extracted from the diseased regions. Those features are then used to feed an SVM. The one-against-one method was used to allow the SVM to deal with multiple classes. The authors concluded that the texture features have the best discrimination potential.

Jian and Wei proposed a method to recognize three kinds of cucumber leaf diseases. As in most approaches, the separation between healthy and diseased regions is made by a simple thresholding procedure. In the following, a variety of color, shape and texture features are extracted. Those features are submitted to an SVM with Radial Basis Function (RBF) as kernel, which performs the final classification.

Fuzzy classifier

The method proposed by Hairuddin et al. [10] tries to identify four different nutritional deficiencies in oil palm plants. The image is segmented according to color similarities, but the authors did not provide any detail on how this is done. After the segmentation, a number of color and texture features are extracted and submitted to a fuzzy classifier which, instead of outputting the deficiencies themselves, reveals the amounts of fertilizers that should be used to correct those deficiencies. Unfortunately, the technical details provided in this paper are superficial, making it difficult to reach a clear understanding about the approach adopted by the authors.

Xu et al. [9] proposed a method to detect nitrogen and potassium deficiencies in tomato plants. The algorithm begins extracting a number of features from the color image. The color features are all based on the b* component of the L*a*b* color space. The texture features are extracted using three different methods: difference operators, Fourier transform and Wavelet packet decomposition. The selection and combination of the features was carried out by means of a genetic algorithm. Finally, the optimized combination of features is used as the input of a fuzzy K-nearest neighbor classifier, which is responsible for the final identification.

Feature-based rules

In their two papers, Kurniawati et al. [15] proposed a method to identify and label three different kinds of diseases that affect paddy crops. As in many other methods, the segmentation of healthy and diseased regions is performed by means of thresholding. The authors tested two kinds of thresholding, Otsu's and local entropy, with the best results being achieved by the latter one. Afterwards, a number of shape and color features are extracted. Those features are the basis for a set of rules that determine the disease that best fits the characteristics of the selected region. Region based object extraction using ANFIS combined with support vector machines discussed by R.Sathishkumar[11]

Zhang [8] proposed a method for identifying and classifying lesions in citrus leaves. The method is mostly based on two sets of features. The first set was selected having as main goal to separate lesions from the rest of the scene, which is achieved by setting thresholds to each feature and applying a weighted voting scheme. The second set aims to provide as much information as possible about the lesions, so a discrimination between diseases becomes possible. The final classification is, again, achieved by means of feature thresholds and a weighted voting system. A more detailed version of S. Annadurai [7] can be found in Alasdair McAndrew [6].

Color analysis

The method proposed by Anup Vibhute, et al. [5] aims to detect and discriminate among four types of mineral deficiencies (nitrogen, phosphorus, potassium and magnesium). The tests were performed using faba bean, pea and yellow lupine leaves. Prior to the color analysis, the images are converted to the HSI and L*a*b* color spaces. The presence or absence of the deficiencies is then determined by the color differences between healthy leaves and the leaves under test. Those differences are quantified by Euclidean distances calculated in both color spaces.

Pugoy and Mariano [4] proposed a system to identify two different types of diseases that attack rice leaves. The algorithm first converts the image from RGB to HSI color space. The K-means technique is applied to cluster the pixels into a number of groups. Those groups are then compared to a library that relates colors to the respective diseases. This comparison results in values that indicate the likelihood of each region being affected by each of the diseases.

IV. Implementation Part:

In this paper we have developed a method by which we can detect weed by using image processing. Then we gave the input of the various diseases affected leaves. By doing so we can reduce the usage of weedicides, thus saving the environment.

If we have two are more types of weeds of different edge frequencies present in the same field. Then the threshold value must be less than the minimum edge frequency of the weeds present. If a small weed is present separately in the field means not in a group then it cannot be detected

because it cannot meet the threshold condition. If both the weed and crop have nearly same edge frequency we should be very careful in selecting the threshold value.
The weed block numbers from the filtering step cannot be block numbers from the filtering step cannot be given automatically to the motor, it has to be done manually. This will take some time.

V. Conclusion:

The wide-ranging variety of applications on the subject of counting objects in digital images makes it difficult for someone to prospect all possible useful ideas present in the literature, which can cause potential solutions for problematic issues to be missed. In this context, this paper tried to present a comprehensive survey on the subject, aiming at being a starting point for those conducting research on the issue. Due to the large number of references, the descriptions are short, providing a quick overview of the ideas underlying each of the solutions. It is important to highlight that the work on the subject is not limited to what was shown here. Many papers on the subject could not be included in order to keep the paper length under control – the papers were selected as to consider the largest number of different problems as possible.

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