V Geetha* et al.
(IJITR) INTERNATIONAL JOURNAL OF INNOVATIVE TECHNOLOGY AND RESEARCH
Volume No.9, Issue No.2, February – March 2021, 9903-9906.

Weed Plant Detection

Dr. V. GEETHA
Assistant Professor, Dept. of CSE, SCSVMV University

Y. PADMINI REDDY
UG Student, Dept. of CSE, SCSVMV University

V. HARIPRIYA
UG Student, Dept. of CSE, SCSVMV University

Abstract: **Knowledge about the distribution of weeds in the field is a prerequisite for site-specific treatment. Optical sensors make it possible to detect varying weed densities and species, which can be mapped using GPS data. The weeds are extracted from images using image processing and described by shape features. A classification based on the features reveals the type and number of weeds per image. For the classification only a maximum of 16 features out of the 81 computed ones are used. Features are used, which enable an optimal distinction of the weed classes.**

The selection can be done using data mining algorithms, which rate the discriminance of the features of prototypes. If no prototypes are available, clustering algorithms can be used to automatically generate clusters. In a next step weed classes can be assigned to the clusters. Such a procedure aids to select prototypes, which is done manually. Classes can be identified, that are distinct in the feature space or which are overlapping and therefore not well separable. Clustering can be used in some, less complex cases to establish an automatic procedure for the classification. Weed maps are generated using the system. These are compared to the result of a manual weed sampling.

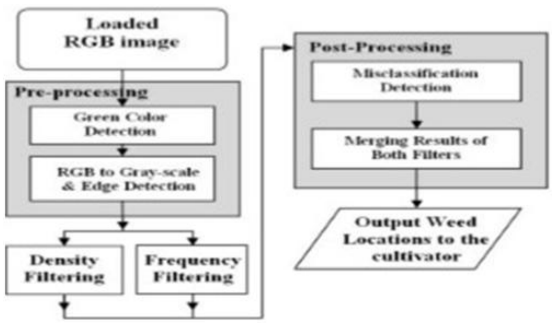
INTRODUCTION

The goal of site-specific weed control is the precise application of herbicides in highly infested areas of a field. Since the distribution of weeds is heterogeneous in most cases and stable across years (GERHARDS et al. 1997, MORTENSEN et al. 1998, GERHARDS & CHRISTENSEN 2003), site-specific weed control can reduce the amount of herbicides used. The spraying has to be controlled by the actual weed infestation. This way the selection and dosage of the herbicides can be optimized for each part of the field.

The first step therefore is to get information about the distribution of the different species. Manual weed sampling is time- and cost-intensive and therefore cannot be economic in a wider practice. SLAUGHTER et al. (2008) give an overview of the techniques for weed detection and find, that the robust weed detection remains the primary obstacle toward commercial development and industry acceptance of robotic weed control technology. Therefore a system was developed to measure the weed infestation.

The spatial heterogeneity of weeds has inspired several weed scientists to study the species distribution of the plants (Wiles et al., 1992; Heisel et al., 1996; Rew & Cousens, 2001; Gonzalez-Andujar & Saavedra, 2003) and different technologies for weed detection, spatial weed management and spatial variable application of herbicides (Gerhards et al., 1997; Christensen & Heisel, 1998; Paice et al., 1998; Gerhards & Oebel, 2006).

EXISTING SYSTEM



PROPOSED SYSTEM

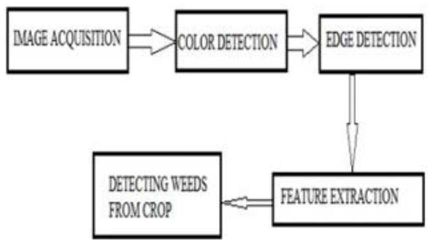


IMAGE ACQUISITION

As mentioned earlier, the first step here is acquiring an image. Here, we considered a field image in a cotton field with top view in a broad day light.

COLOR DETECTION

The weed leaves and the crop leaves are green in color. So, color detection cannot be used here. That is why, we opted for edge detection. But, before going to edge detection we need to separate the green colored part from the image. For this, we need to adjust the HSV values which are specific for each color in HSV table. After this the green colored part is obtained leaving behind the unnecessary soil part. Thus, the obtained green colored part of the image is used for further analysis.

EDGE DETECTION

As mentioned earlier, since the color detection cannot be utilized, we went for edge detection. We have many edge detection filters such as, Canny, SobelX, SobelY, Laplacian, etc. After verifying the edge detection filters we opted for Laplacian filter which gave the following result, but, before passing an image through Laplacian filter the noise in an image must be removed. This is done using Gaussian blur. It not only removes the noise, but also smoothen the image. The Gaussian blur is a type of image blurring filter which can be used in one or more than one dimensions.

FEATURE EXTRACTION

The final and the crucial step here in weed detection is the feature extraction. The prominent feature extraction algorithm in use are SIFT (Scale Invariant Feature Transform) and SURF (Speeded Up Robust Features).

DETECTING WEEDS FROM CROP

We now take the help of key points for feature extraction. Key points acts as accurate points of interest which helps in determining the feature of a desired object. This key point identification is a key step because, in real time the image may get rotated, shrink, translated, or subject to distortion

FLOW CHART AND WORKING PROCEDURE

Image Processing

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them.

Colour Channel Separation

The RGB image is separated into individual red, green and blue images. This separation is done to take only the green component of the leaf. The image is converted only to red, green and blue images

Thresholding

Thresholding is a simple and effective technique used to partition the image into background and foreground. Here "graythresh" is used to convert the green image into global image threshold by using Otsu'smethod

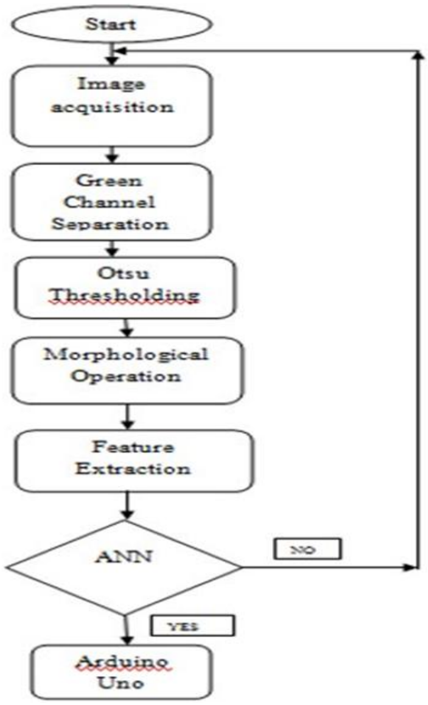
Otsu Thresholding

Otsu's method performs clustering-based image thresholding or the reduction of a gray level image to a binary image. The algorithm assumes that the image contains two classes of pixels following bi-modal histogram (foreground pixels and background pixels), it then calculates the optimum threshold separating the two classes so that their combined spread (intra-class variance) is minimal, or equivalently (because the sum of pairwise squared distances is constant), so that their inter-class variance is maximal. The extension of the original method to multi-level thresholding is referred to as the multi Otsu method.

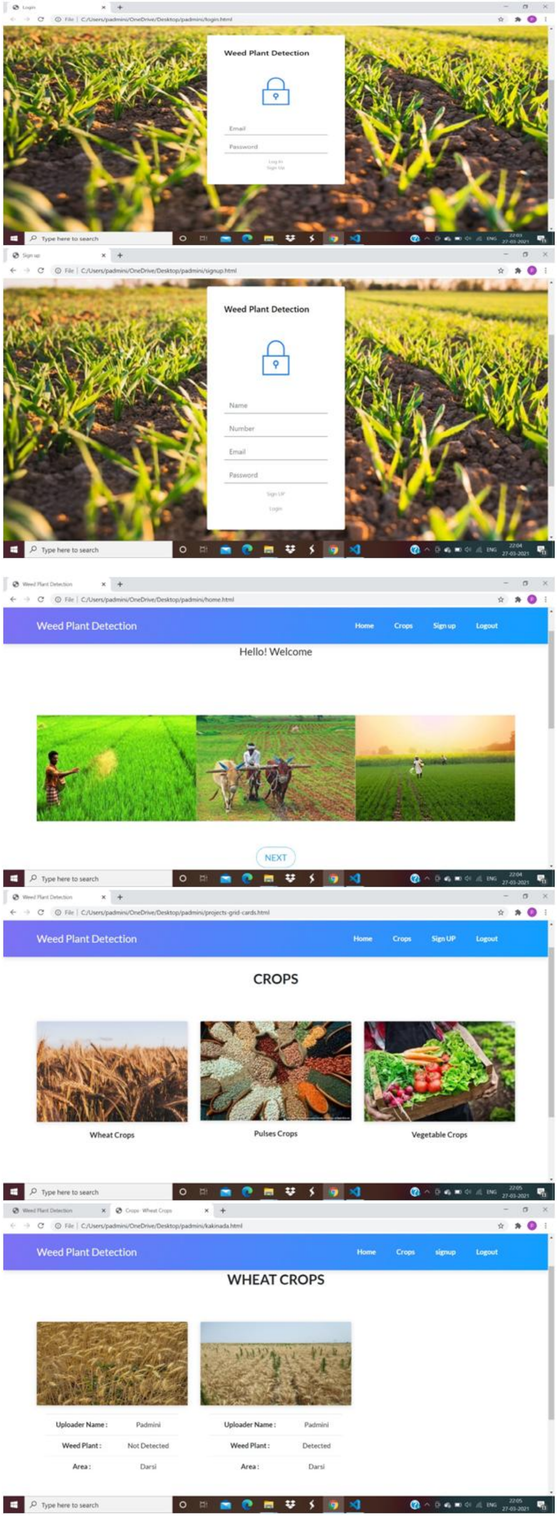
Morphology is a broad set of image processing operations that process images based on shapes. In morphological operation, erosion and dilation is done. Dilation means growing image regions. Dilation is done with the help of imdilate function. Erosion means shrink image regions. Erosion is done using imerode function.

SOFTWARE REQIREMENTS

The software tool we used here is Python3.6.7. Python is one of the prominent languages used for Image processing. It includes certain packages that make Image processing easy to implement. We took help of OpenCV which is an open platform for certain programming languages like C, C++, JAVA, and Python. We have installed certain packages such as Numpy, PyWavelet, Matplotlib, pydot etc. All this work was done on a Windows operating system with an inbuilt Microsoft Visual Studio .



TEST RESULTS:



CONCLUSION

In this system, we have developed a method by which we can detect weed using Image processing. Due to the use of our system, we can detect and separate out weed affected area from the crop plants. The reason for developing such system is to identify and reuse weed affected area for more seeding. This specific area can be considered for further weed control operations, resulting in more production.

Employing the processes like segmentation, feature extraction and clustering can be used to interrogate images of the crops. There is a need to select the most appropriate techniques to assist decision-making. The image processing techniques have been used across a vast range of agricultural production contexts. The accuracy of classification varies depending on the algorithms resolution of images and limitations of image acquisition.

REFERENCES

[1] Mart´ın Abadi, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Ian Goodfellow, Andrew Harp, Geoffrey Irving, Michael Isard, Yangqing Jia, Rafal Jozefowicz, Lukasz Kaiser, Manjunath Kudlur, Josh Levenberg, Dandelion Man´e, Rajat Monga, Sherry Moore, Derek Murray, Chris Olah, Mike Schuster, Jonathon Shlens, Benoit Steiner, Ilya Sutskever, Kunal Talwar, Paul Tucker, Vincent Vanhoucke, Vijay Vasudevan, Fernanda Vi´egas, Oriol Vinyals, Pete Warden, Martin Wattenberg, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng. TensorFlow: Largescale machine learning on heterogeneous systems, 2015. Software available from tensorflow.org.

[2] L´eon Bottou. Large-scale machine learning with stochastic gradient descent. In Proceedings of COMPSTAT'2010, pages 177–186. Springer, 2010.

[3] Zheng Cao, Jose C Principe, Bing Ouyang, Fraser Dalgleish, and Anni Vuorenkoski. Marine animal classification using combined cnn and handdesigned image features. In OCEANS'15 MTS/IEEE Washington, pages 1–6. IEEE, 2015.

[4] Qiang Chen, Mani Abedini, Rahil Garnavi, and Xi Liang. Ibm research australia at lifeclef2014: Plant identification task. In CLEF (Working Notes), pages 693–704, 2014.

[5] Fran¸cois Chollet et al. Keras. https://github.com/fchollet/keras, 2015.

[6] EU Directive. 128/ec of the european parliament and of the council of 21 october 2009 establishing a framework for community action to achieve the sustainable use of pesticides. EU, Brussels, 2009.

[7] Herv´e Go¨eau, Alexis Joly, Pierre Bonnet, Souheil Selmi, Jean-Fran¸cois Molino,

Daniel Barth´el´emy, and Nozha Boujemaa. LifeCLEF Plant Identification Task 2014. In L. Cappellato, N. Ferro, M. Halvey, and W. Kraaij, editors, CLEF2014 Working Notes. Working Notes for CLEF 2014 Conference, Sheffield, UK, September 15-18, 2014, CEUR Workshop Proceedings, pages 598–615. CEUR-WS, 2014.

[8] Itseez. Open source computer vision library. https://github.com/ itseez/opencv, 2015.

[9] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. Imagenet classification with deep convolutional neural networks. In Advances in neural information processing systems, pages 1097–1105, 2012.

[10] Bo Melander, Nicolas Munier-Jolain, Rapha¨el Charles, Judith Wirth, J¨urgen Schwarz, Rommie van der Weide, Ludovic Bonin, Peter K Jensen, and Per Kudsk. European perspectives on the adoption of nonchemical weed management in reduced-tillage systems for arable crops. Weed Technology, 27(1):231–240, 2013.

