Smart Herbicide Sprayer Robot for agriculture fields

G.Bhanumathi[1] B.Subhaker[2]
[1.]Post Graduate student,Deportment of ECE,St Martins Engineering College,Dhulapally Qutbullapur,Hyderabad,Telangana,India
[2.]Assistant Proffesor,St Martins engineering College,Dhulapally Qutbullapur,Hyderabad,Telangana,India

Abstract- The goal of this paper is to develop a new weed detection and classification method that can be applied for autonomous weed control robots. In order to achieve this goal plants must be classified into crops and weeds according to their properties which is done by a machine vision algorithm. Plants growing between rows are considered as weed, while inside a row, where crops are mixed with weeds, a classification method is required. Accordingly in the initial step, plants pixels were segmented from background with an adaptive method which is robust against variable light conditions as well as plant species. After that, crops and weeds were classified according to features extracted from wavelet analysis of the image. Finally, based on positions of weeds, herbicide sprayers are told to spray right on desired spots. The whole algorithm is implemented in embedded systems and keil software which is appropriate for real-time in-field purposes. In order to evaluate the performance of the algorithm corn field images have been taken and selected, overall classification
accuracy of95.89% was achieved.

Index Terms- Weed control robot, machine vision, weed detection, wavelet analysis, LabVIEW

INTRODUCTION

Over the past few years there has been a rising interest in using automation in agriculture as well as other fields. Weed control is one of the areas which demands automation. In conventional weed control systems, herbicides are sprayed uniformly all over the field. Apart from the damaging consequences like negative impacts on plants, soil and underground aquifers, large amount of herbicides will be wasted, as only some parts of fields are covered with weeds.

To prevent these consequences from happening a smart weed control system should be employed. These systems must be capable of locating weed parts of the field and as a result herbicide sprayers are told to spray right on desired spots. In fields, crops are supposed to grow in rows. Based on this assumption any kind of plants that grows within rows should be labeled as weed. But in row situations, crops are mixed with weeds, hence a classification algorithm is also required. Because of wide variety of weed species and lack of a general feature,this task is still an open problem

In order to identify weeds, different attributes have been used in recent papers. One of these attributes is color or spectral retlectance properties. To identify beets among different weed species, Feyaerts and van Gool used a spectrograph camera and up to 86% classification accuracy was reached, although because of using six narrow spectral bands , the scheme was not applicable to in-field purposes. Nieuwenhuizen et al. tried to use color properties of potatoes as a discrimination factor to detect them in sugar beet fields which led to different classification accuracy ranging from 49 to 97 %. By using three wide-band interference filters Piron et al. [4] achieved total classification accuracy of 72% in identifying weeds within carrot rows. Another useful feature is the use of height differences between weeds and desired crop that are achieved through 3D information. First time Sanchez and Marchant discussed the possibility of using such criteria for discrimination purposes however it was limited to in-door conditions. For detecting weeds among tomato plants Nielsen et al. analyzed images acquired by a stereoscopic vision system, but ground irregularities had negative impacts on results. Also there were other researches using height differences.

Apart from these features, another criteria is topological properties of species such as area or curvature. For identifying broad-leaved patches in cereal crops Berge developed a method based on shape parameters and as a result achieved 84 to 90% classification accuracy. Sogaard also used active shape models as a criteria to classify weed species. The problem of this type of method is that it needs ideal conditions, shape of the leaf should be well displayed. Moreover, because of being shape-based and also wide range of species, they cannot be developed to be used for all of them.

The other option is to use textural information of weeds and crops. Meyer was among the first who used texture features as a discrimination factor in weed detection and achieved classification accuracy ranging from 30 to 77% for different species. In addition, system response time of the algorithm was about 20 to 30 seconds which was a significant drawback. Polder and Ahmad also exploited textural features of weed species in order to classify them.

Wavelet transform has been shown to be a promising tool in signal processing. It represents both time and frequency content of a signal and because of this feature can be used to extract textural information of the image.

The goal of this paper is to introduce a new weed detection system based on wavelet transform and as a result of that a real-time autonomous weed control robot can be achieved.

METHODOLOGY

The proposed system is consisted of three main parts. First of all is image acquisition that can be done by any types of digital cameras such as normal webcams. The camera should be installed perpendicular to ground. In this case a webcam was installed on the herbicide sprayer chassis at the height of 1.20 meters above the ground. At this height each output image covers nearly a row and two sides of that which is suitable for the purpose. It should be noted that in order to evaluate robustness of algorithm, image acquisitions were done in the presence of natural variable light conditions. The output images of the webcam were in RGB format with size of 640*480 pixels. After that the acquired images are processed in LabVIEW environment in order to find locations of weeds in the image which will be discussed in detail. The last part is to spray herbicides on desired spots. To do so, electrical nozzles should be installed on the chassis. The number of these nozzles is determined according to the amount of precision required. In this research three nozzles were used, the middle one covers the row and the two others cover sides of the row.

The overall procedure of image processing algorithm is depicted in figure 1 and different steps are discussed in next.

Green segmentation

After the image is captured one of the first steps is to classify the pixels into two categories : plant pixels which include crops as well as weeds, soil. The most well-known vegetation method which was introduced by Woebbecke et al. [15] is called Excess Green (ExG) and was defined as:

$$ExG = 2 \times G - R - B$$

Where R, G and B are the components of RGB color space. This method outlines green parts of the image and the output can be a vegetation image. Figure 2b shows the output of applying this method. As it is obvious this method requires the crops and weeds parts to be completely green which usually does not happen in in-field conditions. Kargar developed a new segmentation method based on auto-clustering. To reduce the influence of light changes, this method extracts hue plane of the image, as this plane is supposed to represent the color of each part. After that a clustering method is applied to the hue plane which is followed by some morphological operation. As figure 3c depicts, the output would be green parts of input image with robustness against light variations as well as different species color.

As it was mentioned in the introduction, at this stage any plant that grows between rows is detected and considered as weed. The rest of the work is dedicated to identify weeds within rows, because they are mixed with crops and a classification algorithm is required (figure 3).

B. Feature Extraction

Goal of this section is to extract proper features, so that weed parts within rows could be distinguished from crops. In corn fields one of the most noticeable properties of corn is type of its leaves which are broad. In comparison with these broad leaves, weed leaves are smaller and narrower. In other words in terms of energy, the amount of activity is much higher in weed parts. To detect these activities one possible solution is to use Fourier transform, as it gives frequency contents of the image. But it is not enough to know just frequency contents of the image and location of each frequency is also needed. To overcome this drawback wavelet transform is exploited which provides both spatial and frequency information.

The wavelet transform has become a useful and promising tool for wide range of signal and image processing purposes. Wavelets are a set of localized basis function with powerful capabilities such as orthonormality, locality in frequency and time domains, fast implementation and maybe compact support [16]. These functions are used to approximate other functions. According to the Mallat's multi-resolution framework [17] linear combinations of orthogonal wavelets $\psi_{m,k}(x)$ can approximate any function $f(x) \in L^2(R)$ as below:

$$F(x) = \sum_{m=-\infty}^{\infty} \sum_{k=-\infty}^{\infty} d_{m,k} \psi_{m,k}(x)$$

$$\psi_{m,k}(x) = 2^{\frac{-m}{2}} \psi(2^{-m}x - k) \qquad m,k \in Z$$

Where k and m are translation and dilation factors of the wavelets respectively. Also approximation can be started from a particular resolution. In case of m=O the equation can be re-

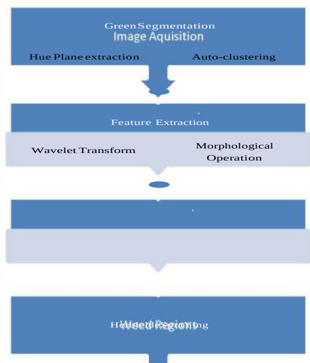
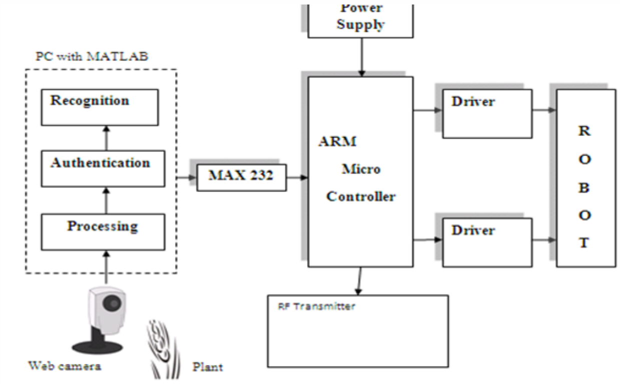


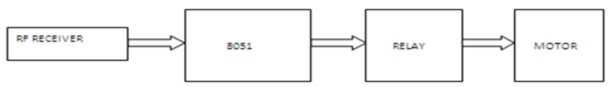
Figure I. the overall procedure of image processing algorithm

These relationships are for one-dimensional case and can be extended to multi-dimensional cases, details can be found

sub-bands coefficients of applying one level wavelet transformation on an image. It can be seen that those parts of the original image that have more variations, have greater intensity levels in sub-bands coefficients and they are exactly weed parts of the image. For having a robust detection of those parts , the histogram of sub-bands are used. Figure 5 illustrates the histogram of HH sub-band of figure 4. It can be seen that most of the pixels have low values which makes it easy to segment the brighter part. Again a clustering technique was used to detect the interval of bright intensities. For instance, in figure 5 the desired interval is between 25 and 255. After applying this threshold on sub-band coefficients and also applying some morphological operations two high-activity and low-activity parts are separated (figure 6). It should be mentioned that at this stage not all the corn pixels are separated which is actually not necessary and is what makes it real-time and robust against small errors, as each nozzle covers a small area and existing of more than a certain number of weeds' pixels in that area means that should be sprayed. This explains why it is not necessary to classify all pixels one by one



Motor section

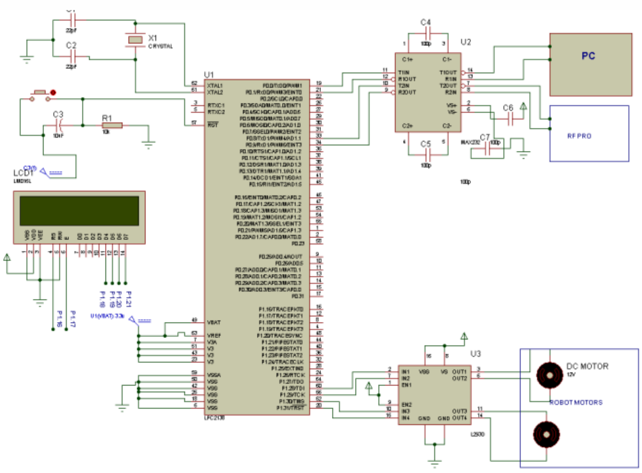


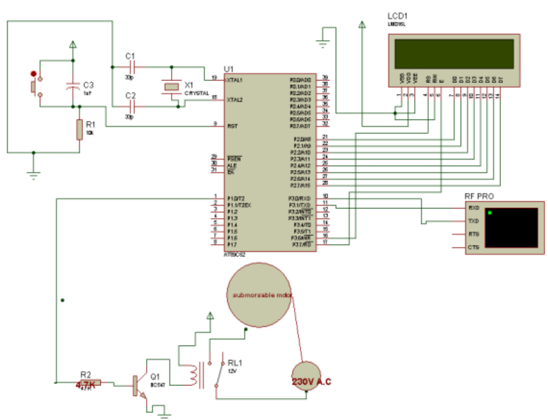
C. Implementation

This paper presents, a robot spray the pesticide for a crop in agriculture fields. A vision-based guidance method is presented to guide the robot platform driven along crops planted in agriculture field. And the offset and heading angle of the platform are calculated by detecting the infected crop automatically using image processing technique in real time. Vision-based guidance is to use camera to detect and identify crop plants and then to find accurate and stable navigation information from the binary image.

The captured image are then processed by using image processing technique, the processed are then converted into voltage levels through MAX 232 level converter and given it to the microcontroller unit. In the microcontroller unit, c language coding is predefined, according to this coding the robot which connected to it was controlled. Robot which has several motors is activated by using the L293D.here zigbee transmitter is used to transmit the colors information. This projectdoesthisapplicationusing wireless concept. One of wireless communication system is RF (Radio frequency) communication system as it is very cheap and very easy to implement. Lpc2148 arm processor is interfaced to the Zigbee . The Zigbee continuously reads the status of the colors information, passes the data to the transmitter and the transmitter transmits the data. At the receiving end, the Zigbee receiver receives this data, gives it to the microcontroller8051. Now, it is the job of the controller to read the data and perform the corresponding action i.e., switch on/off motor

CIRCUITDIAGRAMS





RESULTS AND DISCUSSION

II. The goal is to find weeds in corn fields. In order to evaluate the performance of the algorithm 73 corn field images were selected and were applied as an input of the algorithm. Images were taken in different conditions including sunny sky, cloudy sky, from morning to afternoon. Among these 73 images, 70 of them were classified correctly which yields 95. 89% classification accuracy. Table 1 illustrates a comparison between classification accuracy of proposed algorithm and other methods. It is clear that the proposed technique yields better performance in comparison with th

rest of them. It should be mentioned that the 3 wrong classification were because of over-exposure and lack of any feature in some regions which is related to quality of the webcam, hence it can be improved. In terms of run-time for 640*480 resolution it takes about 160 ms which decreases to 69 ms for 320*240 resolution. These run-times illustrate that the system can be used in real-time situations, as in each process an area of nearly 1.2*1 meters is covered. therefore the run-time is appropriate for a tractor with 20 Km per hour speed which is standard for in-field purposes.

CONCLUSION

In preclSlon agriculture, weed control and detection has become one of the most interesting areas. Preventing damaging consequences of chemical herbicides as well as saving money are some reasons of this trend. This paper introduces a new weed control robot which is capable of identitying weeds in corn fields. With the proposed image processing algorithm 95.89% classification accuracy has been reached. The other feature of this system is being robustness against different light conditions, which is the problem of many weed detection systems, as well as being capable of operating under real-time conditions with the aid of software.

REFERENCES

A. H. KargarBideh, A. Shirzadifar, (2012) "Real-time stereo-vision based herbicide spraying, Proceeding of Iran's third International Conference on Industrial Automation.

Feyaerts, F., van Gool, L. (2001). Multi-spectral vision system for weed detection. Pattern Recognition Letters,22,667-674.

Nieuwenhuizen, A T., Tang, L., Hofstee, J. W., Mu ¨ lIer, J., van Henten, E. J. (2007). Colour based detection of volunteer potatoes as weeds in sugar beet fields using machine vision. Precision Agri- culture,8(6) 267-278.

Piron, A., Leemans, V., Kleynen, 0., Lebeau, F., Destain, M. - F. (2008). Selection of the most efficient wavelength bands for discriminating weeds from crop. Computers and Electronics in Agriculture,62,141-148.

Sanchez, A. 1, Marchant, 1 A. (2000). Fusing 3D information for crop/weeds classification. Proceedings of the 15th International Conference on Pattern Recognition (ICPR'OO) (Vol. 4, p.4295).Los Alamitos,CA: IEEE Computer Society Press.

Nielsen, M., Andersen, H. 1, Slaughter, D. c., Granum, E. (2007). Ground truth evaluation of computer vision based 3D reconstruction of synthesized and real plant images. Precision Agriculture,8(1-2),49-62.

He, D. X., Matsuura, Y., Kozai, T., Ting, K. C. (2003). A binocular stereo vision system for transplant growth variable analysis. Applied Engineeringin Agriculture,19(5),611--617.

Andersen, H. J., Reng, L., Kirk, K. (2005). Geometric plant properties by relaxed stereo vision using simulated annealing. Computers and Electronics in Agriculture,49(2),219-232.

Piron, Alexis, Van Der Heijden, F. Destain, Marie-France .(2011). Weed detection in 3D images. Precision Agriculture,12(5),607-622

Berge, T., Aastveit, A, Fykse, H. (2008). Evaluation of an algorithm for automatic detection of broad- leaved weeds in spring cereals. Precision Agriculture,9(6),391-405.

S0gaard, H. T. (2005). Weed classification by active shape models. Biosystems Engineering,93(3),271-281.

Meyer, G.E., T. Mehta, M.F. Kocher, D.A. Mortensen, A. Sarna!. 1998. Textural imaging and discriminant analysis for distinguishing weeds for spot spraying. Transactions of the ASAE 41(4),1189-1197.

G. Polder et a!. "Weed Detection Using Textural Image Analysis". Plant Research International, PO Box 16, 6700 AA Wageningen,2007.

U. Ahmad, and N. Kondo, "Weed detection in lawn field". http://mama.agr.okayama-u.ac.jp/lase/weed.htmI

D.M. Woebbecke, G.E. Meyer, V. B.K, and D.A Mortensen, "Color indices for weed identification under various soil, residue and lighting conditions". Transactions of the ASAE. v38. 259-269, I995a.

V. Zakeri, V. Naghavi, A A Safavi . Developing real-time wave-net models for non-linear time-varying experimental processes. Computers & Chemical Engineering 0112009;33:1379-1385.

Mallat, S. G. (1989) A theory for multiresolution signal decomposition: the wavelet representation. IEEE Transactions on Pattern Analysis and Mach. Int.,11(7),674--693.

Aknowledgements

B.SHUBHAKER received his master degree in from Jawaharlal Nehru technological university.Present He is working in St Martins Engineering College as assistant proffesor

G.BHANUMATHI received Bachelor Degree from Aurora technological Engineering College in 2011.She is currently pursuing her M. Tech In St Martins Engineering College