



Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources (SSICACR-2017)

<http://aisdau.in/ssicacr>

ssicacr2017@gmail.com

Efficient Pest Detection in Agriculture Using various image processing techniques

Thenmozhi Ganesan

M.C.A.

Madurai Kamaraj University

Madurai, India

maheshthen@gmail.com

Abstract - early disease detection is a major challenge in agriculture field. Hence proper measures have to be taken to fight bio aggressors 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. The propose method in future deals about to reducing the quantity of the fertilizer. Various methods are used to detect the pest from the agriculture plant leafs. The simulation results are showed that accuracy of segmentation of pest from agriculture leaf using various image processing techniques.

Keywords – Agriculture, leaf, disease detection, fertilizer, image processing techniques

I. INTRODUCTION

Agriculture is a spinal card of our country. It is one of the major domains in India and it decides the economy of our country. The total production and economic value of horticultural produce, such as

fruits, vegetables and nuts has doubled over decade period from 2002 to 2012[1].The agriculture production is affected by the natural parameters like rain, flood and Another major parameter which affects productivity of the crop is the pests, disease where the human beings can have control to improve the productivity of crop. Many researches will undergo in this field. The main aim of the researches is to increase the productivity and profit. To increase the productivity and profit, most of the farmers will use more artificial fertilizers to increases the productivity and profit. In modern agriculture, the chemical pesticide is used to remove the pest in the plant. Common pesticides such as DDT, BCH, etc [19].

To increase the productivity and profit two things are very much important. They are detecting the pest automatically and usage of pesticides to recover the pest from the plant. The first thing is detection of pest. But detecting the pest manually is not possible because the pest size is very small and it depends on the plant size. So the automatic detection of the pest is very efficient way to detecting the pest. The second thing is usage of

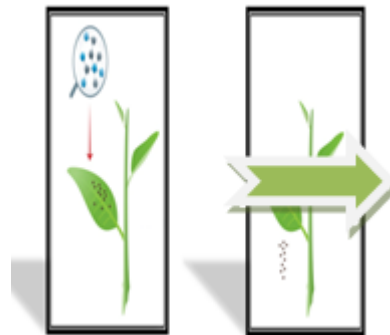
pesticides, but the over usage of pesticides will degrades the soil nutrients and plant nutrients. It affects the human health and animal too [10].

For that reason, this paper deals about reducing the volume of fertilizer for that purpose determine how much about of pesticide is apply to the affected area only. And recover the leaf (or) plant from pest.

Here chili plant is considered [6].The life duration of the chili plant from sowing to the harvesting duration is 180 days. The chili height is 2 to 3 feet. The chili plant is the main horticulture category. In particular period, it becomes a very high demand in the market because the supply is less. However, chili plants fruitfulness should be given importance, because it is not easily affected by all type of pest & diseases. There are a few diseases that could be affected the chili plant through the leaves. The pest affected by the chili plants are aphid, thrips whitefly, lady bug, spider mites.



Fig: 1 Sample chili plant



PROBLEM DESCRIPTION AND CHALLENGES

The design challenges for detecting the pest are

(1) Pest detection is too difficult with respect to the size of plant. If the plant size is very small means the pest presented in the plant size is also small and it is very difficult to detect. The pest affected by the chili plants are whiteflies, aphid, thrips, etc [11]. All whiteflies are suffered from an identity crisis, as they are not “true” flies at all. Their appearance resembles tiny, pure white “moths” but they are in fact, closely related to sap-sucking aphids. Aphid-cast skins can easily be mistaken for whitefly, but whitefly will quickly flutter up and fly away when disturbed. Their quick flight pattern coupled with the fact that they hide on the underside of leaves make them difficult to control. Whiteflies are also prolific because their numbers increase from two to four, four becomes eight, and eight becomes 16 and so on [21].

(2) Detection time of pest in plant region. However, we can't estimate the time for the pest detection. Because of the pest size and the plant size

Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources (SSICACR-2017)

<http://aisdau.in/ssicacr>

ssicacr2017@gmail.com



Fig3: Samples of Pest Affected chili plant

RELATED WORK

[1] Manuel Cabral Reis, Raul Morais, Carlos Pereira, Salviano Soares, A. Valente, J. Baptista, Paulo J.S.G. Ferreira, and J.B. Cruz "Automatic Detection of White Grapes in Natural Environment Using Image Processing"; Springer; 2012. AISC 87; pp. 19-26.

This paper deals about rate of adoption of Precision Agriculture and Precision Viticulture production systems in the Douro Demarcated Region remains low. We believe that one way to raise it is to address challenging real-world problems whose solution offers a clear benefit to the viticulturist. For example, one of the most demanding tasks in wine making is harvesting. Even for humans, the detection of grapes in their natural environment is not always easy. White grapes are particularly difficult to detect, since their color is similar to that of the leaves. Here we present a low cost system for the detection of white grapes in natural

environment color images. The system also calculates the probable location of the bunch stem and achieves 91% of correct classifications.

[2] Cristian Rossi and Esra Erten, "Paddy-Rice Monitoring Using TanDEM-X"; IEEE; 2015. vol.53, no.2, pp.900-910.

This paper evaluates the potential of space borne bistatic interferometric synthetic aperture radar images for the monitoring of biophysical variables in wetlands, with a special interest on paddy rice. The assessment is made during the rice cultivation period, from transplanting to harvesting time (May to October) for fields around Gala lake (Turkey), one of the largest and most productive paddy rice planting area in the country. Detailed ground truth measurements describing biophysical parameters are collected in a dedicated campaign. A stack of 16 dual-pol TanDEM-X images is used for the generation of 32 digital elevation models (DEMs) over the studied area. The quality of the data allows the use of the interferometric phase as a state variable capable to estimate crop heights for almost all the growing stages. The early vegetative rice stage, which is characterized by flooded fields, cannot be represented by the interferometric phase due to a low signal-to-noise ratio but can be easily detected by amplitude and interferometric coherence thresholding. A study on the impact of the polarization in the signal backscatter is also performed. An analysis of the differences between HH and VV DEMs shows the varying signal penetration for the two polarizations at different growing stages. The validation with reference data demonstrates the capability to establish a direct



Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources (SSICACR-2017)

<http://aisdau.in/ssicacr>

ssicacr2017@gmail.com

relationship between interferometric phase and rice growth. The very high coherence of TanDEM-X data yields elevation estimates with root mean square error in a decimetric level, supporting temporal change analysis on a field by-field basis.

[3] Liwen Miao, Yixin Ma, and Junpu Wang, Member, "ROI-Based Image Reconstruction of Electrical Impedance Tomography Used to Detect Regional Conductivity Variation", IEEE; 2014.Vol.63,no.12, pp.2903-2910.

This paper deals about the advantages of noninvasive, fast speed, lowcost and nonionizing radiation hazard have made electrical impedance tomography (EIT) an attractive imaging technology in geological, medical, and industrial applications. However, the EIT image has low spatial resolution due to the limited number of independent measurements and soft-field property. Focused on the fact that, in some applications, the conductivity variation exists only in part of the sensing field, this paper proposes a new strategy to enhance the image quality by restricting the image reconstruction within a region of interest (RROI). Compared with the conventional image reconstruction over the entire sensing field, the proposed strategy of RROI can improve regional image resolution effectively without increasing the number of electrodes and the complexity of the data acquisition system. The implementation of a conventional sensitivity-theorem-based conjugate gradient algorithm with the proposed RROI strategy is presented, and the improvement of image spatial resolution in region of interest is

demonstrated by both simulations and phantom experiments.

[4]Moacir P. Ponti, Jr. "Segmentation of Low-Cost Remote Sensing Images Combining Vegetation Indices and Mean Shift", IEEE ;2013.Vol.10, no.1, pp.67-70.

This paper deals about the development of low-cost remote sensing systems is important in small agriculture business, particularly in developing countries, to allow feasible use of images to gather information. However, images obtained through such systems with uncalibrated cameras have often illumination variations, shadows, and other elements that can hinder the analysis by image processing techniques. This letter investigates the combination of vegetation indices (color index of vegetation extraction, visual vegetation index, and excess green) and the mean-shift algorithm, based on the local density estimation in the color space on images acquired by a low-cost system. The objective is to detect green coverage, gaps, and degraded areas. The results showed that combining local density estimation and vegetation indices improves the segmentation accuracy when compared with the competing methods. It deals well with images in different conditions and with regions of imbalanced sizes, confirming the practical application of the low-cost system.

[5]GrianggaiSamseemoung, PeeyushSoni, Hemantha P.W. Jayasuriya, "Application of low altitude remote sensing (LARS) platform for monitoring crop growth and weed infestation in a



Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources (SSICACR-2017)

<http://aisdau.in/ssicacr>

ssicacr2017@gmail.com

soyabean plantation”; Springer;2012.13(1) , pp.611-627.

This paper is deals about the Crop growth and weed infestation in a soybean field were monitored by processing low altitude remote sensing (LARS) images taken from crane-mounted and unmanned radio controlled helicopter-mounted platforms. Images were taken for comparison between true color (R-G-B) and color-infrared (NIR) digital cameras acquired at different heights above ground. All LARS images were processed to estimate vegetation indices for distinguishing stages of crop growth and estimating weed density. LARS images from the two platforms (low-dynamic and high-dynamic) were evaluated. It was found that crane-mounted RGBC and NIRC platforms resulted in better quality images at lower altitudes (≤ 10 m). This makes the crane-mounted platform an attractive option in terms of specific low altitude applications at an inexpensive cost. Helicopter-mounted RGBH and NIRH images were found suitable at altitudes ≥ 10 m. Comparison of NDVIC and NDVIH images showed that NDVI values at 28 DAG (days after germination) exhibited a strong relationship with altitudes used to capture images (R^2 of 0.75 for NDVIC and 0.79 for NDVIH). However, high altitudes (≥ 10 m) decreased NDVI values for both systems. Higher R^2 values (> 0.7) were also obtained between indices estimated from crane-and helicopter-mounted images with those obtained using an on-ground spectrometer, which showed an adequate suitability of the proposed LARS platform systems for crop growth and weed infestation detection.

[6]Rong Zhou, Lutz Damerow , Yurui Sun , Michael M. Blanke,“Using colour features of cv. ‘Gala’ apple fruits in an orchard in image processing to predict yield”, springer: 2012, 13(2) ,pp.568-580.

This paper deals about the new apple fruit recognition algorithms based on colour features are presented to estimate the number of fruits and develop models for early prediction of apple yield, in a multi-disciplinary approach linking computer science with agricultural engineering and horticulture as part of precision agriculture. Fifty cv. ‘Gala’ apple digital images were captured twice, i.e. after June drop and during ripening, on the preferred western side of the tree row with a variability of between 70 and 170 fruit per tree, under natural daylight conditions at Bonn, Germany. Several image processing algorithms and fruit counting algorithms were used to analyze the apple images. Finally, an apple recognition algorithm with colour difference R - B (red minus blue) and G - R (green minus red) was developed for apple images after June drop, and two different colour models were used to segment ripening period apple images. The algorithm was tested on 50 images of trees in each period. Close correlation coefficients R^2 of 0.80 and 0.85 were obtained for two developmental periods between apples detected by the fruit counting algorithm and those manually counted. Two sets of data in each period were used for modeling yield prediction of the apple fruits. In the calibration data set, the R^2 values between apples detected by the fruit counting algorithm and actual harvested yield were from 0.57 for young fruit after June drop to 0.70 in



Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources (SSICACR-2017)

<http://aisdau.in/ssicacr>

ssicacr2017@gmail.com

the fruit ripening period. In the validation data set, the R2 value between the number of apples predicted by the model and actual yield at harvest ranged from 0.58 to 0.71. The proposed model showed great potential for early prediction of yield for individual trees of apple and possibly other fruit crops.

[7] M. Guijarroa, G. Pajaresb, I. Riomorosc, P.J. Herrerad, X.P. Burgos-Artizzue, A. Ribeiroa, "Automatic segmentation of relevant textures in agricultural images"; Elsevier; 2011,75(1),pp.75-83.

This paper deals about the one of the important issue emerging strongly in agriculture is related with the automatization of tasks, where the optical sensors play an important role. They provide images that must be conveniently processed. The most relevant image processing procedures require the identification of green plants, in our experiments they come from barley and corn crops including weeds, so that some types of action can be carried out, including site-specific treatments with chemical products or mechanical manipulations. Also the identification of textures belonging to the soil could be useful to know some variables, such as humidity, smoothness or any others. Finally, from the point of view of the autonomous robot navigation, where the robot is equipped with the imaging system, sometimes it is convenient to know not only the soil information and the plants growing in the soil but also additional information supplied by global references based on specific areas. This implies that the images to be processed contain textures of

three main types to be identified: green plants, soil and sky if any. This paper proposes a new automatic approach for segmenting these main textures and also to refine the identification of sub-textures inside the main ones. Concerning the green identification, we propose a new approach that exploits the performance of existing strategies by combining them. The combination takes into account the relevance of the information provided by each strategy based on the intensity variability. This makes an important contribution. The combination of thresholding approaches, for segmenting the soil and the sky, makes the second contribution; finally the adjusting of the supervised fuzzy clustering approach for identifying sub-textures automatically, makes the third finding. The performance of the method allows verifying its viability for automatic tasks in agriculture based on image processing.

[8]Xavier P. Burgos-Artizzu, Angela Ribeiro, Maria Guijarro; "Real- time image processing for crop/weed discrimination in maize fields"; Elsevier; 2010,75(2), pp.337-346.

This paper presents a computer vision system that successfully discriminates between weed patches and crop rows under uncontrolled lighting in real-time. The system consists of two independent subsystems, a fast image processing delivering results in real-time (Fast Image Processing, FIP), and a slower and more accurate processing (Robust Crop Row Detection, RCRD) that is used to correct the first subsystem's mistakes. This combination produces a system that achieves very good results under a wide variety of

Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources **(SSICACR-2017)**

<http://aisdau.in/ssicacr>

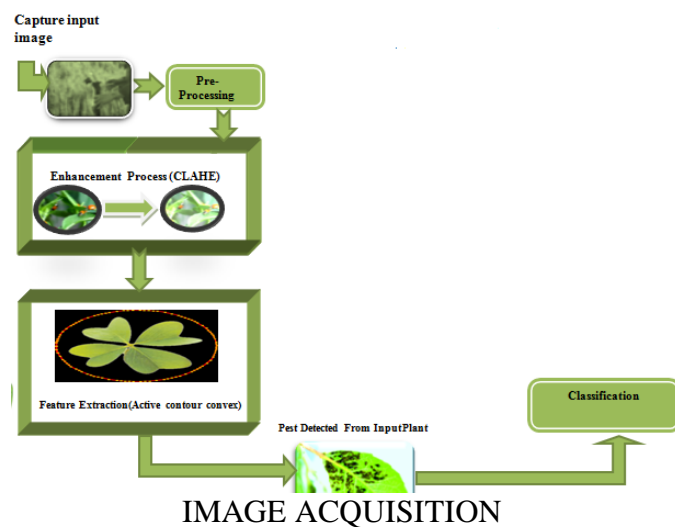
ssicacr2017@gmail.com

conditions. Tested on several maize videos taken of different fields and during different years, the system successfully detects an average of 95% of weeds and 80% of crops under different illumination, soil humidity and weed/crop growth conditions. Moreover, the system has been shown to produce acceptable results even under very difficult conditions, such as in the presence of dramatic sowing errors or abrupt camera movements. The computer vision system has been developed for integration into a treatment system because the ideal setup for any weed sprayer system would include a tool that could provide information on the weeds and crops present at each point in real-time, while the tractor mounting the spraying bar is moving.

Image acquisition in image processing can be broadly defined as the action of retrieving an image from some source, usually a hardware-based source, so it can be passed through whatever processes need to occur afterward. Performing image acquisition in image processing is always the first step in the workflow sequence because, without an image, no processing is possible. The image that is acquired is completely unprocessed and is the result of whatever hardware was used to generate it, which can be very important in some fields to have a consistent baseline from which to work. One of the ultimate goals of this process is to have a source of input that operates within such controlled and measured guidelines that the same image can, if necessary, be nearly perfectly reproduced under the same conditions so anomalous factors are easier to locate and eliminate.

PROPOSED WORK

PROPOSE WORK FLOW DIAGRAM



PREPROCESSING

It will be used for processing the image in the first stage. Then resampling the input image & then processing the image to remove the noise from the image with the help of filters.

This step involves getting the input image and processing the input image. We chose to scan the leaves when flies were not very active. Samples were manually cut and scanned directly in the plant.

Once the image is acquired and scanned the next step is to implement image processing techniques in order to get the information about the pest. It is executed as follows; Object extraction is followed by feature extraction. Object extraction itself



Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources (SSICACR-2017)

<http://aisdau.in/ssicacr>

ssicacr2017@gmail.com

decomposes into a sequence (background subtraction, then filtering, and finally segmentation).

Since background subtraction 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. The second sub-operator, filtering may be performed. The next operator, segmentation, also corresponds to a choice between two alternative sub-operators: region-based and edge-based. 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.

OBJECT EXTRACTION

A. Background Subtraction

Background subtraction is a commonly used class of techniques for segmenting out objects of interest in an 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: $f(x, y) > T \dots(1)$ is called an object point, otherwise it is background point. A threshold image $g(x, y)$ is defined as:

$g(x, y) = 1$ if $f(x, y) > T \dots(2)$ and $g(x, y) = 0$ if $f(x, y) \leq T \dots(3)$.

B. 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 a 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.

C. 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



Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources (SSICACR-2017)

<http://aisdau.in/ssicacr>

ssicacr2017@gmail.com

analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, texture. ROI (Region of Interest) algorithm is used for the segmentation process.

Here we using various methods like Improved Kmean clustering, C mean clustering method, FCM & OTSU methods with various parameters like mean, average etc.,

ENHANCEMENT

Enhancement is the modification of an image to alter impact on the viewer. Generally enhancement distorts the original digital values; therefore enhancement is not done until the restoration processes are completed.

CONTRAST ENHANCEMENT

There is a strong influence of contrast ratio on resolving power and detection capability of images. Techniques for improving image contrast are among the most widely used enhancement processes. It is important to utilize the entire brightness range of the display medium. Here CLAHE is used to enhance the image.

CLAHE

CLAHE will makes the image quality as high resolution, because it is used for the conversion of the image quality as low resolution to high resolution and then it will operates on small regions in the image, called tiles, rather than the entire image. Each tile's contrast is enhanced, so that the histogram of the output region approximately matches the histogram specified by the distributor parameter. The neighboring tiles are then combined using bilinear interpolation to eliminate artificially induced boundaries. The contrast, especially in homogeneous areas, can be limited to avoid amplifying any noise that might be present in the image.

FEATURE EXTRACTION

ROI: Region of Interest algorithm is used for the feature extraction. ROI is that part of the image which catches our attention instantly than the other part of the image. It is highly diagnostic area and there is no lossless. ROI is encoded with higher quality than background.

This algorithm is better for analysis the error or any different region in image. It has a greater sensitivity and functional resolution.

RESULT AND ANALYSIS

Various methods of pest detection are analyzed with visual and parameter analysis like as follows



Fig: Improved K mean K-Mean method



Fig: Fuzzy method OTSU method

Performance of Improved K means parameters like

$$\text{MSE} = 0.7202$$

$$\text{Mean Square Error} = 0.7202$$

$$\text{Peak Signal to Noise Ratio} = 28.6688$$

$$\text{MNormalized Cross-Correlation} = 0.8530$$

CONCLUSION

Early detection and extraction system was presented, different image processing techniques were used to detect and extract the pests in the captured image. The presented system is simple and yet efficient. It used background modeling to

detect the presence of insect pests in the captured image, and Gaussian filter was used to remove the noise from the input image. Various mechanism used to extract the detected objects from the image is simple by using contour convex for segmentation. It allows us to accurately distinguish the pests and leaves. This is an important step towards the identification of pests and to take the corresponding remedies. In future, a single advanced technique which works in detecting the different types of pests

REFERENCES

- [1] Cristian Rossi and EsraErten, "Paddy-Rice Monitoring Using TanDEM-X"; IEEE; 2015.
- [2] Liwen Miao, Yixin Ma, and Junpu Wang, Member, "ROI-Based Image Reconstruction of Electrical Impedance Tomography Used to Detect Regional Conductivity Variation", IEEE; 2014.
- [3] Moacir P. Ponti, Jr. "Segmentation of Low-Cost Remote Sensing Images Combining Vegetation Indices and Mean Shift", IEEE; 2013.
- [4] Manuel Cabral Reis, Raul Morais, Carlos Pereira, Salviano Soares, A. Valente, J. Baptista, Paulo J.S.G. Ferreira, and J.B. Cruz "Automatic Detection of White Grapes in Natural Environment Using Image Processing"; springer; 2012.
- [5] GrianggaiSamseemoung, PeeyushSoni, Hemantha P. W. Jayasuriya, "Application of low altitude remote sensing (LARS) platform for monitoring crop growth and weed infestation in a soyabean plantation"; Springer; 2012.
- [6] AnupVibhute, S K Bodhe; "Applications of Image Processing in Agriculture: A survey;



Alagappa University, Karaikudi, India

15th -16th February 2017

IT Skills Show & International Conference on Advancements in Computing Resources (SSICACR-2017)

<http://aisdau.in/ssicacr>

ssicacr2017@gmail.com

International Journal of Computer Applications”;
2012.

[7] Rong Zhou, Lutz Damerow , Yurui Sun , Michael M. Blanke, “Using colour features of cv. ‘Gala’ apple fruits in an orchard in image processing to predict yield”, springer: 2012.

[8] M. Guijarroa, G. Pajaresb, I. Riomorosc, P.J. Herrerad, X.P. Burgos-Artizzue, A. Ribeiroa , “Automatic segmentation of relevant textures in agricultural images”; Elsevier; 2011.

[9] Xavier P. Burgos-Artizzu, Angela Ribeiro, Maria Guijarro, Gonzalo Pajares; “Real- time image processing for crop/weed discrimination in maize fields”; Elsevier; 2010.

[10] HosseinNejati, ZohrehAzimifar, Mohsen Zamani; “Using Fast Fourier Transform for weed detection in corn fields”; IEEE; 2008.

[11] Alasdair McAndrew; “Introduction to digital image processing with MATLAB”; course Technology; 2004.