Design of an Embedded System based on Machine Vision for Autonomous Weed Control Applications

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Abstract

Precision agriculture seeks modern technologies to lower the cost of farming application automations. This paper proposes a real-time crop detection system designed for an embedded autonomous weeding machine. The system uses a modern pattern recognition methodology implemented on a cost-effective portable hardware platform. Maize seedlings do not have certain geometric pattern. Therefore, the proposed methodology employs advanced machine vision and learning techniques for irregular pattern recognition and object classification aligned for rapid field crop inspection. The algorithm is mainly based on Viola-Jones framework and optimizes the computational efficiency and response time over the parameters such as cultivator travel speed, weed emergence, lighting conditions, plant morphological and growth variation, camera view angle and height, and etc. All analysis process is performed on a single-board computer with an on-board camera.

Since maize breeders in Antalya prefer a commercially affordable within-row weeding machine, the proposed system is tested over a maize land. The weed/crop discrimination results of classifier training on a typical local crop row under a common lighting condition indicate a satisfactory performance for regular cultivator travel speeds.

Keywords: Maize crop detection, embedded system design, machine learning, single board computer

1. Introduction

The modern trend in engineering is briefly lowering labor's job by automation, environment protection, higher efficacy and lower costs. In particular, in agricultural applications, a proposed technology can be verified if it can be properly implemented for a real field performance, since it faces live creatures, varying conditions and unexpected circumstances.

This study presents a design of a cost-effect system capable of real-time crop plant detection to serve the abovementioned purpose. In other words, development of a portable visual detector with low cost helps design and manufacturing of a fully autonomous weed controller that is affordable for local farmers. As maize industry grows in Antalya, maize breeders more and more welcome modernization in their corn fields.

2. Literature Review

Hand weeding is a labor intensive and cost-ineffective job (Cordill, 2011; Kunz et al., 2015) and thus needs adoption of a technology (Bontsema et al, 1998). There are numerous researches on robotic weeding since 1981 (Slaughter et al. 2007) and it is still a challenge for scholars in agricultural robotics (Assirelli et al. 2015).

Recent global concerns about adverse impact of herbicides on environment and human as well as herbicide-resistant weeds have motivated researches for automatic weeding systems (Bakker et al., 2010; Gobot et al. 2013; Beckiea & Tardif, 2012; Fennimore et al., 2013). Within the presented systems for automatic agriculture operations, vision systems have been widely used and performed more satisfactorily for real-time detection on the field (Pourreza et al. 2015; Rovira-Más et al. 2010). During the past decade, almost all engineering fields have favored machine vision technology and agricultural engineering is not an exception. Machine vision technology has attracted the scholars' intention for weed management and dozens of international projects are devoted for such an intention using different methods and strategies (Tellaeche et al. 2008; Burgos et al., 2009; Guerrero, 2012; Guijarro et al., 2011; Montalvo et al., 2012; Onyango & Marchant, 2003).

Obviously, precise detection of crop plants and seedlings species helps distinguishing between the intended crop plant and all other crop plants to carry on a satisfactory weeding. Hence, dozens of algorithms and techniques have been proposed for crop plant identification taking into account different field machine and parameters such as camera pose and cultivator forward speed as well as natural illumination, plant distances and growth stage (Taufik Ahmad, Tang & Steward, 2014; Midtiby et al. 2016). However, the most challenging task is still discrimination crop plants and within-row weeds. The features vary remarkably on the field inasmuch as one may say that neither of the crop plants on the same crop field resembles the other one. This problem will be worsen when a typical sowing is performed by local farmers since the grown plants may have different leaves due to the growth stage and most importantly leaf angle against the camera inasmuch as common methods of machine vision for object detection encounter a complete failure. One common practice for enhancing detection accuracy has been using distance between crop plants and thus Chen et al. (2013) and also Cordill & Grift (2011) relied upon recognition of crop foliage by pre-presentation of the distance between adjacent plants.

The current state of the art in this area is discussing mechanical weeding systems. Real-time visual detection for field perception and convenient for mechanical automatic weeding application is studied by Rovira-Mas et al (2010). Intelligent mechanical weed control machines capable of within-row weeding have been presented by Garfords Robocrop (Garford, 2011) and the Robovator by F. Poulsen Engineering (Frank Poulsen Engineering, 2014).

The aforementioned systems achieved the capacity of up to 4 ha h^{-1} for mechanical in-row weeding. However, on the one hand, the offered systems yet, have been either very expensive or sophisticated that farmers can barely afford. On the other hand, they are either designed for intra-row application or they necessarily require an accurate crop spacing pattern or LIDAR device (Midtiby et al. 2016). In other words, if the adjacent crop plants are not sown by a certain distance from each other due to a farmer job (such as Aksu maize fields in Antalya, Turkey) then the system produces a complete failure. Furthermore, in our knowledge, using such a smart system for various field crops (not only for vegetables) has not been publicized yet.

Apart from that, the advent of new technology in the past two years in the single board computers and embedded systems alleviated the chance of developing affordable intelligent systems for local farmers. The price, size and power consumption of single board computers on the field are sufficiently declined, and their processing delay is tackled by weeding vehicle forward velocity due to shorter crop plants spacing. Indeed, because of global increasing demand for more agricultural product over the same land, the crop plants spacing is getting shorter, which requires a further weed/crop discrimination accuracy and lower travel speed.

3. Materials and Methods

Weeds can be categorized as every plant other than the aimed crop. Moreover, real-time detection requires particular computational and processing equipment. Therefore, the main task will be development of a detector capable of discriminating maize and non-maize plants via low expenses and low computational load method. Single board computers such as Raspberry Pi 2 (RPi2) are very good candidate for this purpose. The processing speed and other corresponding important factors must be taken into account.

In brief, the proposed design is a system that utilizes face detection cascade classifier for within-row maize plant detection on a regular non-weeded corn field in Antalya. The program is written in C^{++} language and compiled on Debian Jessie (Linux-based operating system) by CMake compiler. Moreover, for the main part of this study as maize plant identification, OpenCV API is employed.

We would like to see the performance of the system using not-identical maize image samples captured on a different corn field, with different natural illumination and different growing stage. The only sensor to be used is a single lens camera and thus the input information is limited to a stream of two dimensional images.

3.1. Embedded Systems Employed in Precision Agriculture

On-field maize identification is computationally effective, easy to implement and portable for agricultural application on a cost-effective machine is a complex task (Tillett, 2007). Hence, most of the requirements and limitations were studied to come up with a machine that should employ computationally efficient processing technique (Vibhute and Bodhe, 2012). Dozens of software and hardware such as plugins and peripherals recently delivered were examined to see which one outperforms the others. Furthermore, during the past decade, even in-use technologies have been much more developed comparing with the project e.g. Tillett and Hague Technology Ltd project in Silsoe in 2001 (Tillet and Hague, 2014). Indeed, the technology advancement in detection application programming interface, its integrated development environment, operating system, processing platform and vision devices has provided much cheaper electrical machines. Moreover, since an overall system of on-field maize detector has not been presented yet in the literature, the present study focuses on development of a practical system design and on top of that the proposed detection method will be evaluated.

3.2. The System Components

Agility and system simplicity and industrial attributes are the heart of system design. Recently, the advent of single board computers has changed the course of real-time detections. As an instance, in Gainesville, at a similar climate to Antalya, and for a similar application at the precision agriculture laboratory at University of Florida, OpenCV classes are being used on a platform of BeagleBone Black by Dr. Lee and his research team (Sengupta, 2014; Garg, 2015).

The proposed system is physically comprised of a Raspberry Pi 2, Pi-camera module and a power bank of 2 A. Indeed, comparing with Android and Windows devices, system based on single board computers will not get expensive and are salable to farmers (Garg, 2015). Since RPi has quick video capturing from Pi-camera module and it is cheaper and has higher capacity is higher and, thus a Raspberry Pi 2 (RPi 2) was employed which poses similar operational properties to BeagleBone Black (e.g. Linux kernels) while poses more technical information available on internet (Table 1).

Indeed, RPi is a single board computer aimed for image processing (IP) jobs and has a module fabricated for image processing projects since vision is a key component for our live video stream processing. Figure 1 shows how the system is mounted for a real-time application test.

Table 1. Properties of the utilized single board computer, RPi 2

CPU	A 900MHz quad-core ARM Cortex-A7
RAM	1GB
USB	4 ports
GPIO	40 GPIO pins
Screen and Video output	Full HDMI port composite video Display interface (DSI)

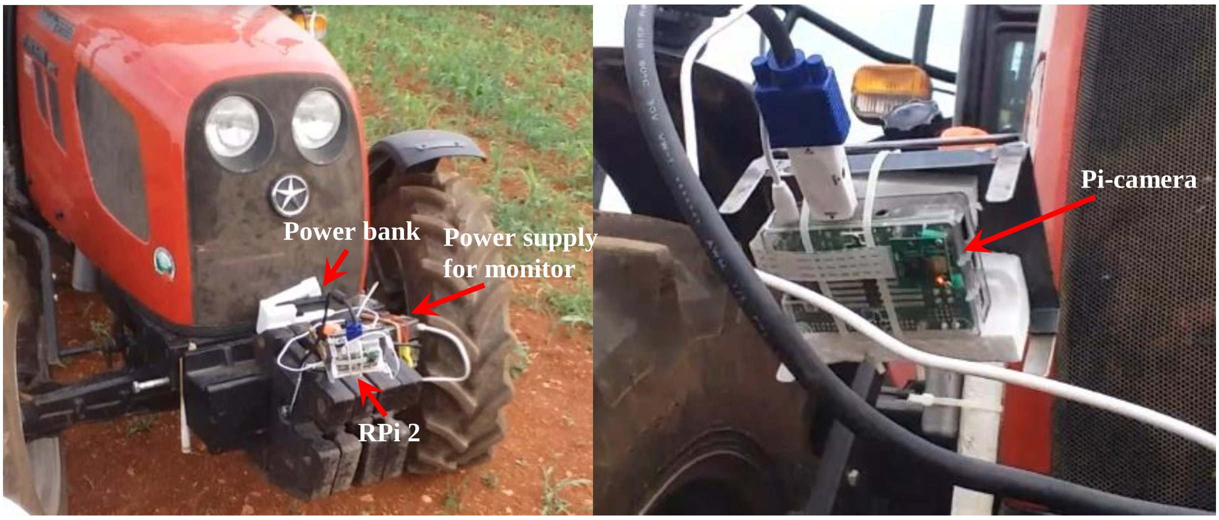

Figure 1. The system mounted on the tractor on a field test; left) the complete view of power bank, monitor power supply and single board computer; Right) Raspberry Pi 2 and Pi-camera connected to a regular monitor to observe the performance

3.3. Software interface specifications

The latest standard operating system for RPi 2 is Debian Jessie and thus peripheral installation was carried out more precisely. In particular, digital SLR camera integration into the Linux based IDEs as well as mounting a camera module and using via video4Linux packages required special tricks to be stable for continues use. In order to develop a real-time detector, both C^{++} and Python are evaluated since Debian poses corresponding compiler and then they were compared with the ones in Microsoft environment.

For classifying plant algorithm, since maize on field does not have a certain geometric pattern to be recognized machine learning techniques are required to train the algorithm based on maize plant features on available images, (Apron et al., 2009).

Indeed, working on real-time object detection limits research options due to the required short response-time (Weis et al. 2009) concern and thus several successful algorithms such as morphological identification, blob detection, RGB to HSV color space transformation and filtration were discredited whereas solely grayscale images gives rapid response for our purpose (Romeo et al. 2012). Moreover, some concurrent processing such as segmentation or filtration before the main detection process costs time at least about a couple of seconds and thus dropped from the list. Variety of OpenCV versions were tested for their performance stability and 2.4.9 was chosen for detector development.

Detection for plant canopy and mature leaves is much more satisfactory while weed problem is for seedlings. Therefore, detector should discriminate weeds and maize seedlings having similar patterns (Vrindts et al. 2002).

As mentioned in the introduction, automatic visual detection for agricultural applications, has interested many research centers around the globe such as precision agriculture laboratory in University of Florida who are conducting a complete system a fully autonomous horticultural machine using BeagleBone Black and OpenCV (U of F, PA lab, 2016).

The system design has a limitation as computer's memory. Hence the algorithm has to take into account number of pixels, rate of frame capturing and size of scene being monitored by camera. Research in this area has a limitation due to crop planting season limitations because tests can be performed in the particular crop leaf stages which limit research options. There are numerous parameters that influence the detection and weed control performance and thus a test on real agricultural field is inevitable.

3.4. Real-Time Crop Plant Detector Algorithm

Real-time plant classification poses particular difficulties that arise from the vast majority of plant morphology although maize canopy has particular specifications on its leaves. Moreover, outdoor lighting conditions are very remarkable concern (Steward, 1999) and thus feature-based cascade classifier is employed as an effective object detection method proposed thus far. It can work as a rapid object detector using a boosted cascade of simple features for multiple object detection on a live video stream.

One may notice that the algorithm must be capable of multiple feature classification and object detection. Cascade classifier as the best candidate for real-time maize detector development was trained via the training utility of OpenCV for creating samples and feature deduction which has recently employed local binary pattern method and become remarkably rapid.

After this classifier gets trained, it can be applied to a region of interest (the same size as used during the training) in an input image or stream of images. Simply speaking, the classifier helps signaling a digit such as one if the region is likely to show the object as maize canopy and zero otherwise. To search for the maize canopy in the whole image one can move the search window across the image and check every location using the classifier. The classifier is designed so that it can be easily resized in order to be able to find the maize canopies of interest at different sizes or point of view for capture which is more efficient than resizing the image itself. Thus to find an object of an unknown size in the image the scan procedure should be done several times at different scales.

Figure 2 demonstrates the detection algorithm. One method to remove the noises in the spectrum of the whole images is automatic removal of everything except the green parts, so-called color threshold. Figure 3 demonstrates the training procedure. Training is the core of weed control and thus this part takes the most time. Moreover, it cannot be automatically conducted and a human should make the maize plant images selection and cropping if it is required for both after and before the segmentation of sample images. The training was carried out on a system having a core-i 2 processor, 32 bit OS and 4 GB RAM. The cascade file was trained eventually using Local Binary Pattern method (LBP) whereas it was capable of processing higher quality images (90^2 – 100^2 pixels) and also it was couple of hours faster for training ratio index of 3×10^{-5}.

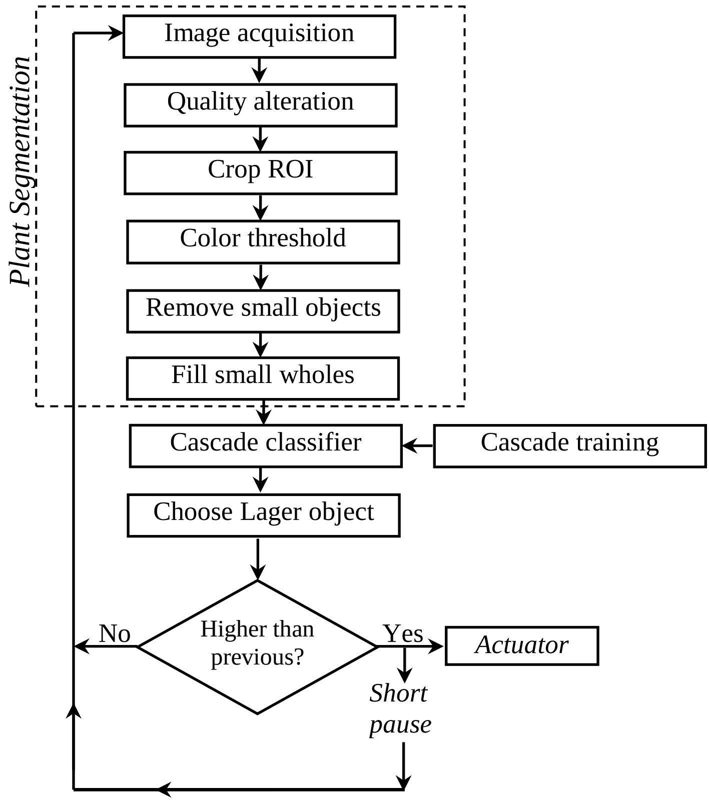

Figure 2. The algorithm used for the real-time crop plant detection

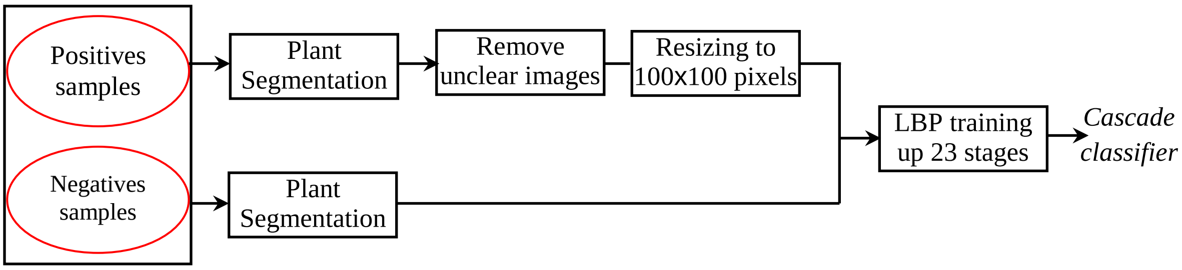

Figure 3. Tarining procedure using selected and cropped positive images and seleting negative sample images; within segmentation some of the images in which the background could not be clearly removed were eliminated from the sample images.

Assuming typical configuration used by Garford (2011), Figure 4 demonstrates the entire weed control system. The key parameters are anticipated as camera pose and tractor's forward speed and thus for this purpose we ran a test on the maize field. Comparing the present classifier that is based on cascade training with classifiers based on Random Forest, it is obviously expected to observe higher processing speed and less accuracy, however experimental tests are required for verifications.

Figure 4. Maize field comditions used for the tests; Left) light intensity of the test day, a regular tractor, and the proposed system mounted on Right) the colse view of the not-weeded farm filed

4. Results and Discussion

The results obtained from the preliminary tests interest the researcher on this field whereas the expected meaningful relation among parameters and the detection performance. In addition, the system is expected to work accurately and immediately, and thus sometimes a trade –off is required to achieve both of them at a reasonable cost of each. Indeed, there are numerous parameters affecting the detection process that will be discussed here.

The Pi-camera captures video frames at satisfactory rate for the next step of image processing. The good point is that camera vibrations on the field had almost zero effect on the images processing.

On the corn field, the tests were carried out and it was observed that the illumination is the most significant interference. Indeed, doing a test on outdoor conditions is far different from test under controlled circumstances. In order to have a faster real-time detection, all video frames will be converted into grayscale. Therefore, under very sunny lighting conditions, the large part of maize leaves will appear extremely bright and thus in the grayscale conversion they become almost a different pattern, that is difficult to be recognized even by human even though, crop plants' shadows were well removed from the image in the color-threshold stage.

The second import parameter with similar importance is camera pose. Camera's height and angle play a key role in detection. In our test, we followed the similar manner of the previous studies such as Garford (2011), however, the height is shorter in order to keep the camera closer to the crop plants, whereas the plants growth stage is different and occlusion of neighbor plants or other leaves of the same plant might occur. The best way to take picture for processing is capturing through the front view; however this is impossible on the crop field due to the problem of hitting the plants and destroying them. Apart from that, one maize will be seen behind the other one either in the same row or adjacent in the image. Moreover, whereas an in-row weeding is aimed, maize row detection is not required. Within the field tests, it was observed that detection performs more satisfactorily if the camera's angle is set to 40^o against the horizon.

The left top image in Figure 5 show the maize image capturing on a field in a sunny day. Similar images were used for training cascade classifier. The left bottom image in Figure 5 shows the scene used in detection tests. After segmentation the very right images in Figure 5 were obtained using binary image as a filter and then a histogram equalized grayscale process. The top image shows an undesirable illumination while the bottom shows an almost perfect lighting condition for an image processing job. The very right images show that the system is capable of a proper color thresholding.

Figure 6 is a picture captured while working on the field. Since the hoeing actuator is not connected yet for weed control performance observations, thus the timing signals are outputted on the black screen on the left hand side of Figure 6.

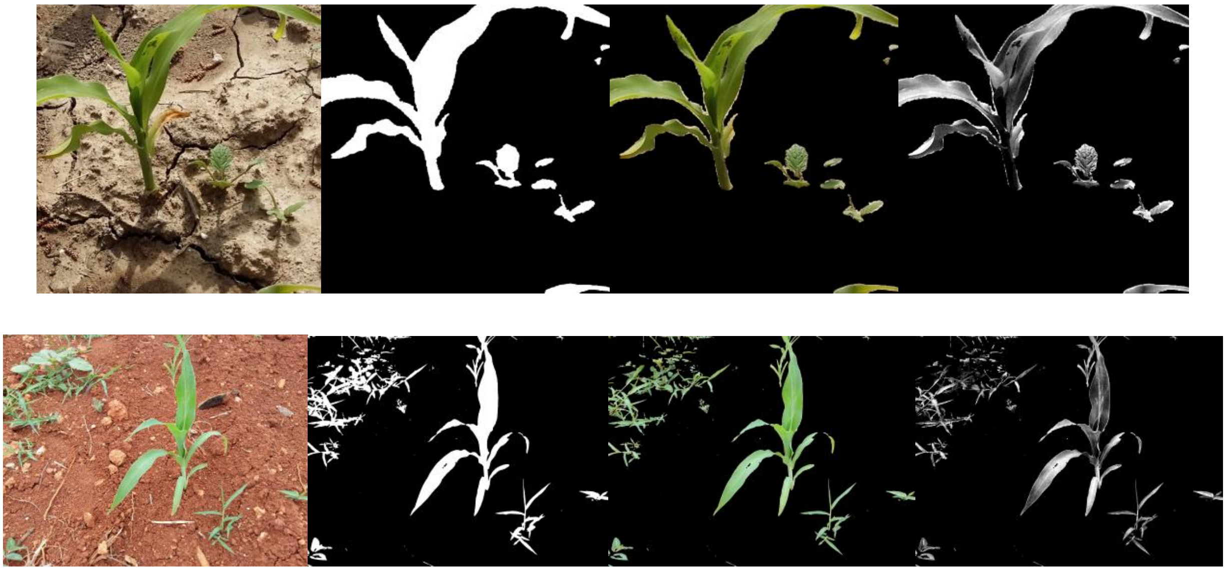

Figure 5. Segmentation of two maize scenes. Very right image are the original view while the rest demonstate the vision of machine on the field. Upper right image was captured in a different field having different lighting conditions and used as positive samples for trainings. Lower right image was captured in an excellent lighitng condition.

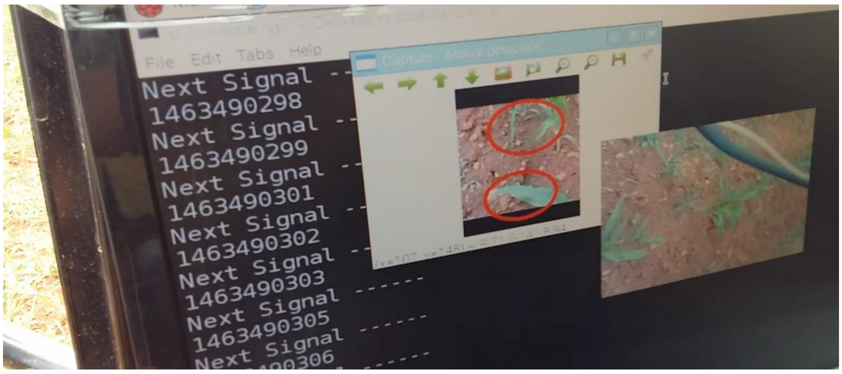

Figure 6. Observation of the real-time performance of the proposed detection system using machine vision on the maize field. The right window is the original image (camera is rotated) and the left window is the outcome. On the black screen the timing signals are depicted to be used for future weeding actuation.

The image quality acquired by the program is significant since if it is set to 640x480 pixels, the delay will increase up to 40 seconds and interestingly reducing pixels to 60% will lower the delay to less than three seconds. Furthermore, the region of interest (ROI) must be chosen and also camera pose must be reset accordingly. In other words, the system can perform optimally if detection of only one maize plant is considered at once.

Although the tractor's forward speed above the 8 km/h moves the maize plants quickly in video, it can be solved by using the aforementioned settings on the program. Detections were performed more satisfactorily for the speeds less than 8 km/h.

It was observed that discrimination between maize and weed was not satisfactory in a general free condition. In other words, as it was demonstrated in the algorithm description section, other techniques must accompany the discrimination process. Hence, maize plants size and in-row distance were exploited. Maize plants were sown with at least about 10 cm distance from each other. In addition, maize plant normally has a larger size in the image comparing with weeds in the same image. These characteristics were a key point in in-row maize detection.

The delay has been of concern computer scholars particularly when image will go under further edition such as filling the small whole and removing small parts from the background, since the RPi 2 processor capacity and memory are remarkably lower than a regular PC (Table 1). It was observed that dilating and eroding had no meaningful delay impact on the detection procedure. Maize row detection is a very helpful aid in detecting the maize plant; however in this study the intra-row plants were not included in the region of interest. Moreover, binary images have lighter computational weights neither in training nor in detection and thus do not applied for either of them.

During the trainings, it was observed that negative samples play keys role in discrimination between maize and non-maize plants. Obviously using wide variety of non-maize plants and scenes and also including similar species with similar size weed plants will significantly enhance the detection accuracy.

Since the system detect a part of the plant (mostly one leaf) and the location of a single leaf is different from the whole maize, thus it is needed to use a timing relaxation factor according to the 2-D location and size.

The detection failure is mostly due to the difference between the maize plants used for the training and maize plants in the test whereas growth stage, species, illumination and soil background are different. On top of all, leaves angle widely vary. In other words, it is like inverting a human face in an image and expecting face detection. Consequently, real-time crop plant detection is a subtle task and requires further information from the crop field into account for working properly.

5. Conclusions

In this study a system design for real-time crop plant detection is proposed and tested. The results of the tests indicated a satisfactory performance considering special setting on the field. It was observed that if the system is set by a particular manner it will perform more satisfactory. In other words, it is recommended to use the cascade classifier on RPi 2 platform, and for maize plants with height of not more than 35 cm, and in-row sown distance of at least 15 cm, Camera height and angle to about 70 cm from the ground, and 40^o against the horizon, respectively; tractor forward speed not more than 8 km/h; the image captured on real-time from Pi-camera on the crop field cropped to the region of interest of single maize plant with less plant occlusion in each detection, or alternatively, the quality of the image altered to the half size, (150x200 pixel image is more recommended).

It is also recommended to use other low-cost sensor to determine (or at least estimate) the tractor velocity and maize distances.

Obviously, the accuracy will be improved using indirect sun illumination (e.g. cloudy weather) for both trainings and detection tests. Despite the expectations tractor vibrations while working on the crop field had a minor contribution to detection error. However, the steady move of tractor will play significant role for future actuation signaling. Furthermore, the power bank is recommended to be used which endures more than 11 hours for working on the field that is reasonable for a typical large field e.g. on North America.

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