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Smart Robotic Weed Control System for Sugar Beet

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ABSTRACT

While weeds in sugar beet farming reduce crop yield and quality, they also lead to higher labor and material losses. In recent years, in order to eliminate or reduce the damage caused by weeds in sugar beet farming, weed control has gained importance. To this end, various studies have been conducted on robotic weed control by detecting weeds using image processing algorithms and hoeing or spraying the weeds. In this study, weeds in sugar beet fields were detected by the image processing algorithm and were sprayed with a liquid. When height of spraying nozzle above the ground was 30 cm and 50 cm, measurements of spraying robot were carried out for 8 different speeds. The weed surface covering area of spraying liquid was evaluated by two different methods. A decrease of 40% in nozzle height of smart spraying robot caused a decrease of about 12.18% at 4 different weeds surface covering area (cm^2) of spraying liquid and a decrease of 16.70% at weed surface covering area (pixels) of spraying liquid.

Keywords: Image processing, Herbicide application, Precision agriculture, Precision spraying.

INTRODUCTION

The significance of weed control in agricultural crop production is an undisputed issue. The use of moisture, nutrients, and sunlight by weeds rather than the crop plants has a detrimental effect on crop yields and quality unless controlled (Slaughter *et al*., 2008).

These days, there is a clear option to reduce the use of chemicals in agriculture. Many technologies have been developed to raise the safety of agricultural products and to reduce their adverse effects on the environment, and precision agriculture is a precious component of the framework to achieve this aim (Zhang *et al*., 2002; Stafford, 2006).

The development of autonomous vehicles and robotic technology in bio-production systems have been examined by many research groups to optimize complex agricultural operations relevant to precision weed management. An autonomous platform is included in the examples for robotic weeding (Astrand and Baerveldt, 2002; Bakker e*t al*., 2010), a precision spraying system (Gil *et al*., 2013; Sabanci and Aydin, 2013; Tewari *et al*., 2014), an automatic device for non-chemical control of pests (Tillett *et al*., 2008; Perez-Ruiz *et al*., 2012; Perez-Ruiz *et al*., 2014).

With the help of technological advancements, today, the automatic classification of weeds and plants by computer vision has an increasing attention in the literature (Arribas *et al*., 2011). For example, the classification of plants into either crop or weeds by a few relevant machine vision algorithms makes the performance of mechanical weeding or the application of herbicide possible (Yang *et*

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al., 2000; Cho *et al*., 2002; Aitkenhead *et al*., 2003; Burks *et al*., 2005). The detection of geometrical, textural or other statistical features by digital images forms the basis of machine vision methods (Alchanatis *et al*., 2005).

Machine vision is processed for weeds in sugar beet in studies carried out by Jafari *et al*. (2006). They benefited from image data used in discriminant analysis according to the relation of 3 basic components (blue, red, green image) that make up true colors of different plants. They used 300 digital images of sugar beet plants and 7 types of common sugar beet plants in different light conditions to see discriminant analysis procedure and to provide adequate information.

Habib *et al*. (2007) made weed classification by image processing methods in their study. Control of the microcontroller unit providing image processing and herbicide application were made with a Personal Digital Assistant (PDA). This study was carried out with various weeds in the laboratory. In the study which was carried out by taking 70 samples from each of narrow and broad-leaved weeds and 140 samples in total, a success rate of 97% was obtained in the classification of weeds.

Ismail *et al.* (2010) developed a system in their work that made online automated detection of weed and spraying. This system makes spraying by detecting weed automatically and precisely. Also, the system determines the intensity and exit points of weeds as in real time. After the start of spraying applications, webcam primarily captures images of weeds. The computer software determines RGB values in the form of pixels. These values were used in comparison of RGB values of weeds, of which real images were captured during the spraying, with RGB values used as reference. Nozzles open or close depending on the density and percentage of green pixel value of weeds.

Sabanci and Aydin (2014) determined the weeds between rows in sugar beet fields by using image processing techniques and a model of variable level herbicide application was applied on them with precision spraying robot developed during the study. When the nozzle height of precision spraying robot was 30 cm and its speed of was 8.928 cm s^{-1}, in a pesticide application on an area of 1.6 m^2, a decrease rate of 55.22% in herbicide usage was achieved when compared to conventional pesticide applications. The amount of spraying liquid applied on weeds by precision spraying robot with 8 different speeds was measured. It was found that increasing the speed of the spraying robot caused a decrease in the amount of spraying liquid applied on weeds.

Kumar and Thamizharasi (2015) studied the control of robots and provided 4 different gestures for controlling the robots, i.e. forward, -backward, left, and right. To cut weeds, a gripper concept using buttons is anticipated. These movements are given by the user-using Microelectromechanical Systems (MEMS) accelerometer which will be set by hand. MEMS will recognize the mechanical movement of the hand whenever the hand moves in some direction. This mechanical hand movement is translated into equivalent electrical signals by MEMS and sent to the peripheral interface controller (PIC) microcontroller. Control signals are sent to the receiver through radio frequency (RF) transceiver by the PIC microcontroller at the transmitter side. These signals are received at the receiver area by the controller and gives direction to the robot. This robot type is used in the crop filed to cut the weeds as per the user command.

There are many studies on spraying by detecting weeds with image processing algorithms in literature. But any studies about the weed surface covering area of spraying liquid at various speeds of the robot according to the situation of spraying nozzle height were not observed. The objective of this study was to detect the weeds between rows of sugar beet by using image processing techniques with a developed smart spraying machine and spray the weeds with a liquid (inked water).

MATERIALS AND METHODS

In the study, a smart spraying robot, composed of spraying unit, control unit, cameras and laptop was developed (Figure 1). Four wheels (6 cm diameter) were used for movement of the spraying robot. Spraying robot was moved back and forth by means of a steel rope of 0.4 mm on a rail of 5 m in length.

Movement of smart spraying robot on rail was provided with 3-phase asynchronous motor of 0.75 kW. The inverter that controlled the engine speed was Delta brand, EL series, VFD015EL21 models, with a power of 1.5 kW.

In spraying unit, a 0.75 kW, 8 bar pressure pump was used to spray herbicide applied on weeds from spraying nozzle. 80 microns jet rodding check valve nozzle was used as the spraying nozzle (Figure 2).

The system was controlled with a programmable logic controller PLC which changed the status of the valves according to the signals coming from the laptop, and enabled the control of the speed of spraying robot and the information coming from the limit switches, Delta brand DVP-14SS2 series, had relay outputs. To take the images of sugar beet plants and weeds in real-time and transfer those to Matlab software, Logitech C905 webcam equipped with CCD sensor was used (Figure 2). The pictures of sugar beet (*Beta vulgaris* L.) were taken in a field (38° 9' 24.78" N 31° 40' 32.74" E) at Doğanhisar district of Konya in Turkey.

The lamb's quarters (*Chenopodium album*), musk thistle (*Carduus nutans*), prickly lettuce (*Lactuca serriola*), and cockspur grass (*Echinochloa crus-galli*) in the sugar beet fields were selected as weeds to be used in our study. Black inky water (spraying liquid) was used to spray on weed.

Image process as a general term means manipulation and analysis of an image information. (Castleman, 1996). Image processing is used in fields such as industry, security, geology, medicine, and agriculture. It is used for color analyses and classification, observing the root growth, measuring leaf dimensions, detecting weeds, and similar purposes (Keefe, 1992; Trooien and Heermann, 1992; Perez *et al*., 2000; Dalen, 2004; Jayas and Karunakaran, 2005).

To choose the plant on the image taken by the webcam on precision disinfection robot, it is separated into RGB channels and green color value is obtained using Equation (1) (Ramaraju and Kumar, 2014).

$$F= (G-0.5)\times(R-0.5)\times B \qquad (1)$$

In this Function (F), the aim is to get the closeness of the color to green. To get the green color data, Red (R) and Blue (B) color values were multiplied by 0.5 and subtracted from the Green (G) value.

Instead of using the whole picture taken

Figure 1. General view of the precision spraying robot.

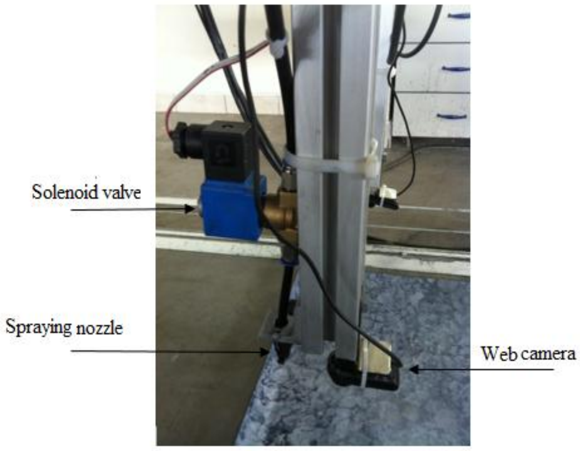


Figure 2. Solenoid valve, spraying nozzle and web camera.

from the webcam, only a part of 100×100 pixel is used. In order to apply the herbicide precisely, the disinfection process is started when the weed is under the nozzle. If the green color level is greater than a certain threshold, the disinfection liquid is sprayed on the weed.

The amount of liquid is increased according to size of the plant. In Figure 3, the Matlab screen view of the inter row weed control and disinfection are shown.

For the picture to be processed efficiently and quickly, it must be converted to black and white model, which is the basic model. As brightness value of each gray image will vary depending on atmospheric conditions and environmental conditions, it is important that the threshold be set as a variable.

Otsu's thresholding algorithm is used to find this variable threshold level (Otsu, 1979). The found threshold level is a brightness parameter between 0 and 1. Once this threshold is found, the gray image is converted to black.

Think gray levels in an image as {0, 1, 2, …, V-1}. The existence number of each pixel in the image number is n_v, the number of pixels in the image is *N*. The probability distribution functions of the pixels are calculated as follows.

$$P_v = \frac{n_v}{N} \quad P_v \geq 0 \quad \sum_{V=0}^{V-1} P_v = 1 \tag{2}$$

$$\mu_T = \sum_{V=0}^{V-1} vP_v \tag{3}$$

Where,

n_v = v the number of repetitions of the pixel values in the image.

N = Total number of pixels in the image;

P_v = *v* Probability density function of the pixel,

μ_T = Mean of the total probability density function.

When we separate pixels with a k threshold to two different classes as ω_0 *ve* ω_1, we can express the total and average/mean values according to probability distribution function using Equations (4) and (5).

$$\omega_0 = \sum_{V=0}^{k} P_v \text{ and } \mu_0 = \frac{1}{\omega_0} \sum_{V=0}^{k} vP_v \tag{4}$$

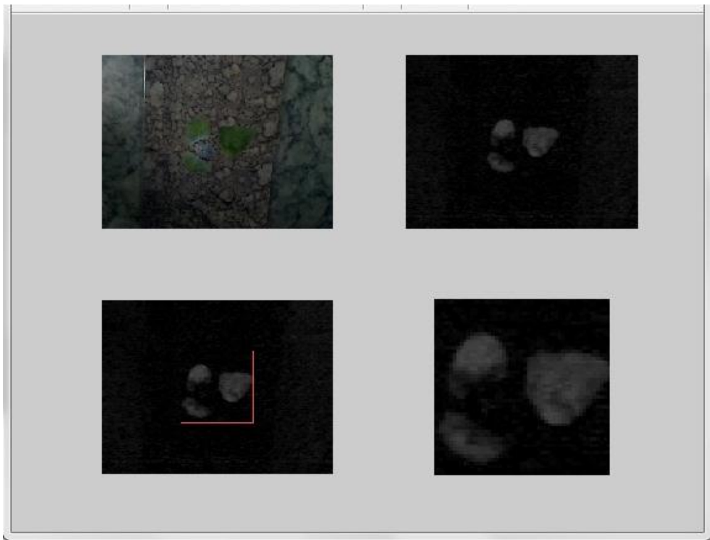


Figure 3. Matlab screenshot of spraying between rows.

$$\omega_1 = \sum_{V=k+1}^{V-1} P_v \text{ and } \mu_1 = \frac{1}{\omega_1}\sum_{V=k+1}^{V-1} vP_v \quad (5)$$

Equation (6) was offered by Otsu to measure the accuracy of threshold value which was found

$$\eta = \frac{\sigma_B^2}{\sigma_T^2} \quad (6)$$

The equality variance among the classes is calculated with Equation (7).

$$\sigma_B^2 = \omega_0(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2 \quad (7)$$

The total variance is calculated with Equation (8).

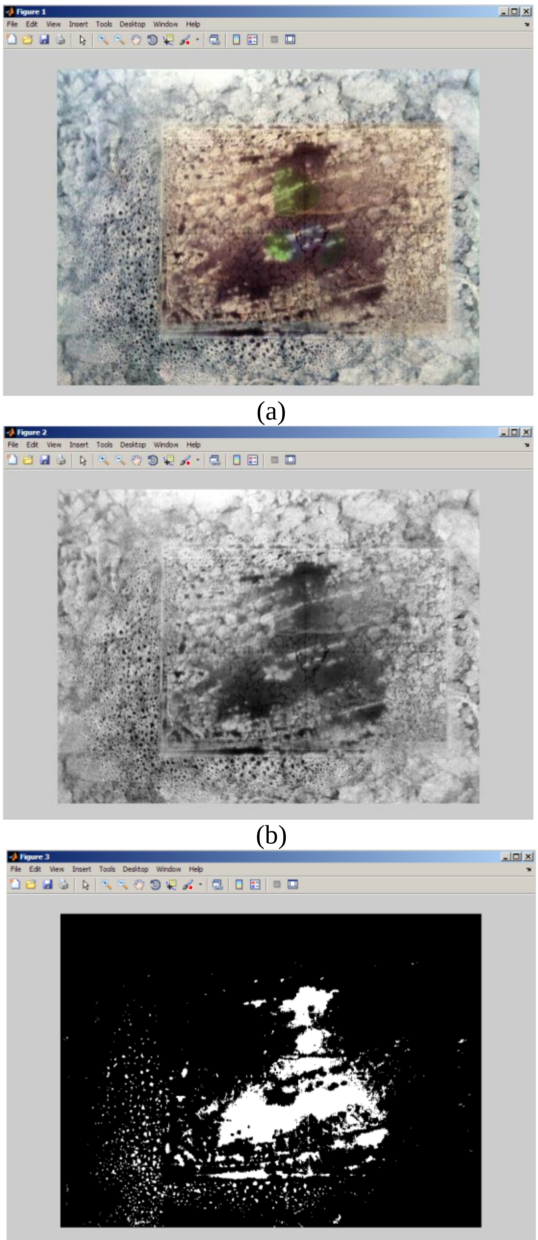
$$\sigma_T^2 = \sum_{V=0}^{V-1}(v - \mu_T)^2 P_v \quad (8)$$

Here, as a result, the k value that makes the η value (6) maximum is searched and this value is taken as the optimal threshold value (Otsu, 1979).

Tests were made by adjusting the height of the spraying nozzle on smart spraying robot 30 cm and 50 cm above the ground. Covering areas of spraying liquid on the surface of weeds was evaluated by two different methods.

In the first method, spraying liquid applied on weeds was applied for 8 different speed values by placing weed pictures on rails on which smart spraying robot moved and images were photographed from the same height. Later, these pictures were converted to gray level image (Figure 4) and then they were converted to black and white image by using Otsu method, the pixel area value of field, where the spraying liquid were applied, was evaluated with *bwarea* command.

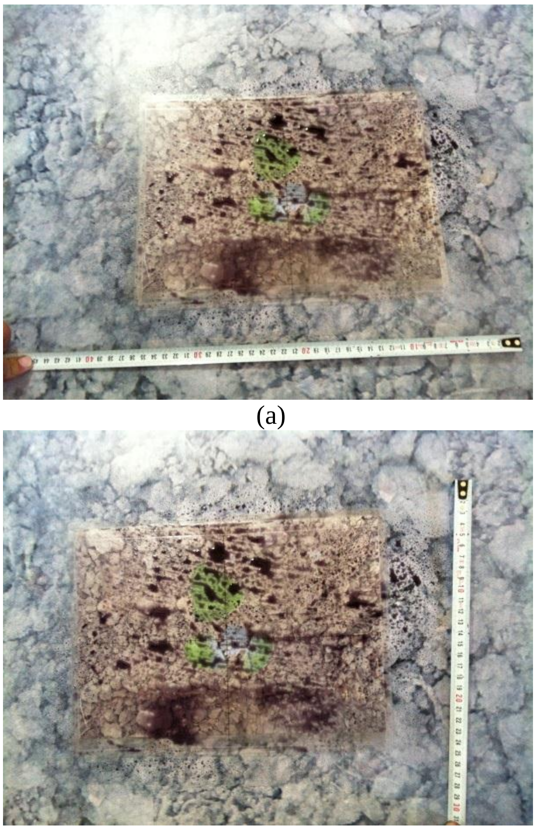
In the second method, the area for spraying liquid used on weed was evaluated as rectangle. To calculate the area of spraying liquid, the inky water length on movement direction of spraying robot and the spraying work width were measured using a graduated tape (Figure 5). Multiplying the measured length by the measured width, the coverage areas were calculated.



(a) (b) (c)

Figure 4. Spraying fluid field measurements (pixels): (a) Lamb's quarters (*Chenopodium album*) on which spraying liquid was applied; (b) Gray level image on which spraying liquid was applied, and (c) Binary image on which spraying liquid was applied.

When height of spraying nozzle to ground was 30 cm and 50 cm, tests for spraying robot were carried out for 8 different speeds.



(a)

(b)

Figure 5. Spraying liquid field measurement (cm^2): (a) The length of the spraying robot on the direction of movement, and (b) Spraying working width.

In these tests, covering areas of spraying liquid on surface of weeds was evaluated by using two different methods.

RESULTS

Tests were made by adjusting the height of the spraying nozzles on smart spraying robot 30 cm and 50 cm above the ground. Spraying liquid applied on weeds was applied at 8 different speed values (2.232, 4.469, 6.329, 6.711, 8.928, 12.944, 19.607, 25.806 cm s^{-1}) by placing weed pictures on rails on which smart spraying robot moved and images were photographed. Areas covered by spraying liquid on the surface of weeds was evaluated by two different methods.

The speed of spraying robot and the covering area were inversely proportional. When the speed of the spraying robot increased, the number of frames taken by the webcam decreased. Weeds were determined using image processing algorithms. When the system detected a weed, Matlab transferred information to PLC, which triggered solenoid valve and applied inky water on lamb's quarters (Chenopodium album). When the number of frames captured by webcam decreased, the shooting time of solenoid valve became shorter. Because the application time of spraying liquid was shortened, the covering area decreased. Flow chart of inter row weed spraying is given in Figure 6.

When the spraying nozzle height of smart

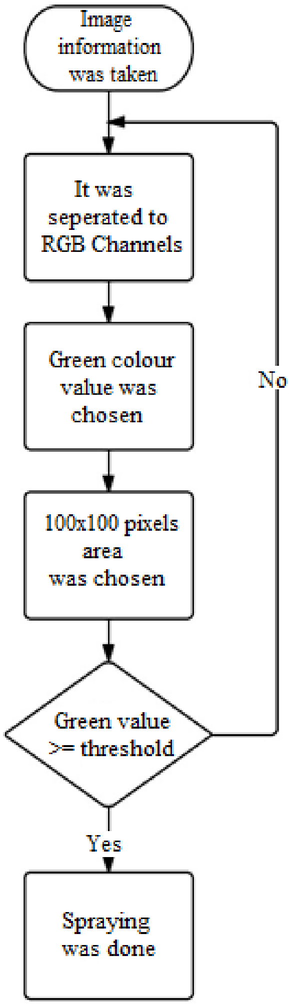


Figure 6. Flow diagram of spraying weeds between rows.

spraying robot was 50 cm and its speed increased from 4.469 to 6.711 cm s^{-1}, this caused a 50% increase in its speed and a decrease in spray liquid covering area (cm^2): for lamb's quarters (*Chenopodium album*) 9.33%, musk thistle (*Carduus nutans*) 9.64%, prickly lettuce (*Lactuca serriola*) 9.04%, cockspur grass (*Echinochloa crus-galli*) 13.88%. When the speed of spraying robot increased from 4.469 to 8.928 cm s^{-1}, i.e. a 100% increase, a decrease in spray liquid covering area (cm^2) was observed: lamb's quarters (*Chenopodium album*) 15.67%, musk thistle (*Carduus nutans*) 19.76%, prickly lettuce (*Lactuca serriola*) 15.17%, cockspur grass (*Echinochloa crus-galli*) 20.45% (Figure 7).

When the spraying nozzle height of smart spraying robot was 30 cm and its speed increased from 4.469 cm/s to 6.711 cm s^{-1}, this caused a 50% increase in its speed and a decrease in spray liquid covering area (cm^2): for lamb's quarters (*Chenopodium album*) 9.49%, musk thistle (*Carduus nutans*) 9.67%, prickly lettuce (*Lactuca serriola*) 8.41%, cockspur grass (*Echinochloa crus-galli*) 14.24%. When the speed of spraying robot increased from 4.469 to 8.928 cm s^{-1}, i.e. a 100% increase, a decrease in spray liquid covering area (cm^2) was observed: lamb's quarters (*Chenopodium album*) 15.69%, musk thistle (*Carduus nutans*) 19.08%, prickly lettuce (*Lactuca serriola*) 15.28%, and cockspur grass (*Echinochloa crus-galli*) 20.57% (Figure 7).

When the speed of smart spraying robot was 8.928 cm s^{-1} and the spraying nozzle height was decreased from 50 to 30 cm, a 40% decrease in spraying nozzle height, a decrease in spray liquid covering area (cm^2) was recorded: lamb's quarters (*Chenopodium album*) 12.25%, musk thistle (*Carduus nutans*) 11.73%, prickly lettuce (*Lactuca serriola*) 12.37%, and cockspur grass (*Echinochloa crus-galli*) 12.38% (Figure 7).

When the spraying nozzle height of smart spraying robot was 50 cm and its speed

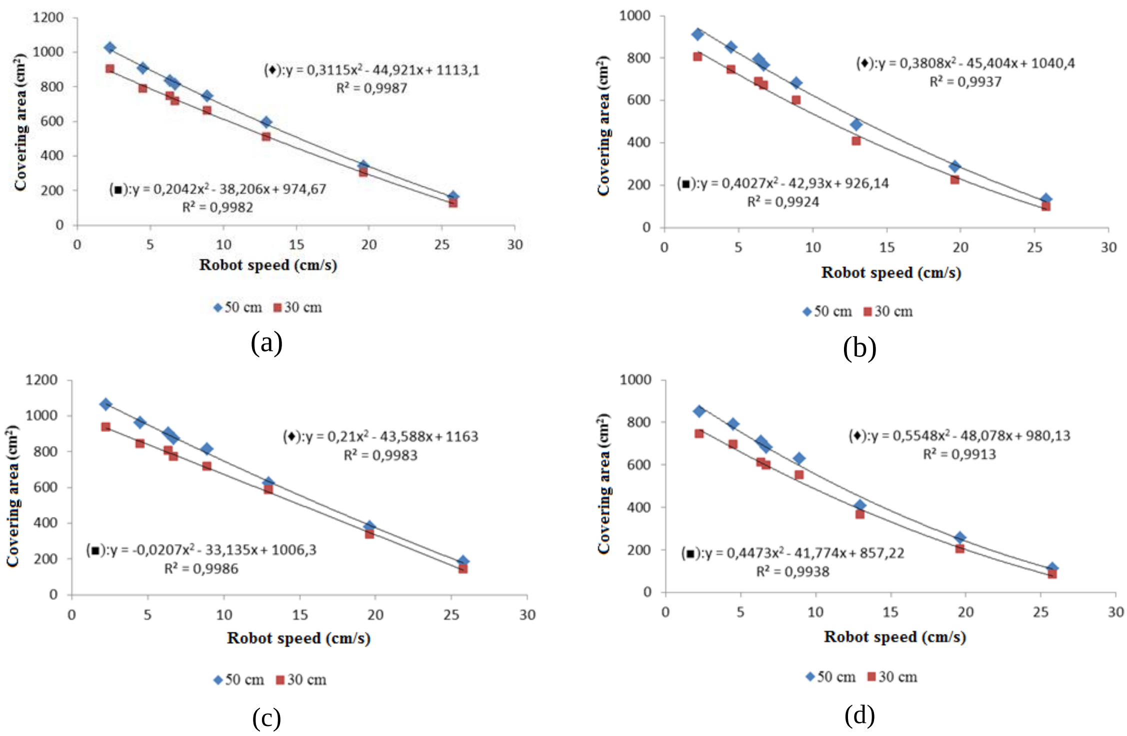


Figure 7. The change of coverage area (cm^2) depending on the speed for weeds: (a) Lamb's quarters; (b) Musk thistle; (c) Prickly lettuce, and (d) Cockspur grass.

increased from 8.928 to 12.944 cm s^{-1}, this caused a 44.98% increase in its speed and a decrease in spray liquid covering area (pixels): for lamb's quarters (*Chenopodium album*) 14.54%, musk thistle (*Carduus nutans*) 20.4%, prickly lettuce (*Lactuca serriola*) 13.65%, and cockspur grass (*Echinochloa crus-galli*) 23.8%. When the speed of spraying robot increased from 12.944 to 25.806 cm s^{-1}, i.e. a 99.36% increase, a decrease in spray liquid covering area (pixels) was observed: lamb's quarters (*Chenopodium album*) 40.05%, musk thistle (*Carduus nutans*) 35.65%, prickly lettuce (*Lactuca serriola*) 38.33%, and cockspur grass (*Echinochloa crus-galli*) 32.92% (Figure 8).

At 30 cm height of the spraying nozzle of smart spraying robot and increasing the speed from 8.928 to 12.944 cm s^{-1}, i.e. 44.98% increase in its speed, caused a decrease in spray liquid covering area (pixels): for lamb's quarters (*Chenopodium album*) 14.93%, musk thistle (Carduus nutans) 21.84%, prickly lettuce (*Lactuca serriola*) 18.63%, and cockspur grass (*Echinochloa crus-galli*) 29.81%. When the speed of spraying robot increased from 12.944 to 25.806 cm s^{-1}, a 99.36% increase, a decrease in spray liquid covering area (pixels) was observed: lamb's quarters (*Chenopodium album*) 38.89%, musk thistle (*Carduus nutans*) 38.25%, prickly lettuce (*Lactuca serriola*) 40.41%, and cockspur grass (*Echinochloa crus-galli*) 35.88% (Figure 8).

When the speed of smart spraying robot was 12.944 cm s^{-1} and the spraying nozzle height was decreased from 50 cm to 30 cm, i.e. a 40% decrease in spraying nozzle height, the spray liquid covering area (pixels) decreased: lamb's quarters (*Chenopodium album*) 14.27%, musk thistle (*Carduus nutans*) 20.76%, prickly lettuce (*Lactuca serriola*) 14.61%, and cockspur grass (*Echinochloa crus-galli*) 17.19%

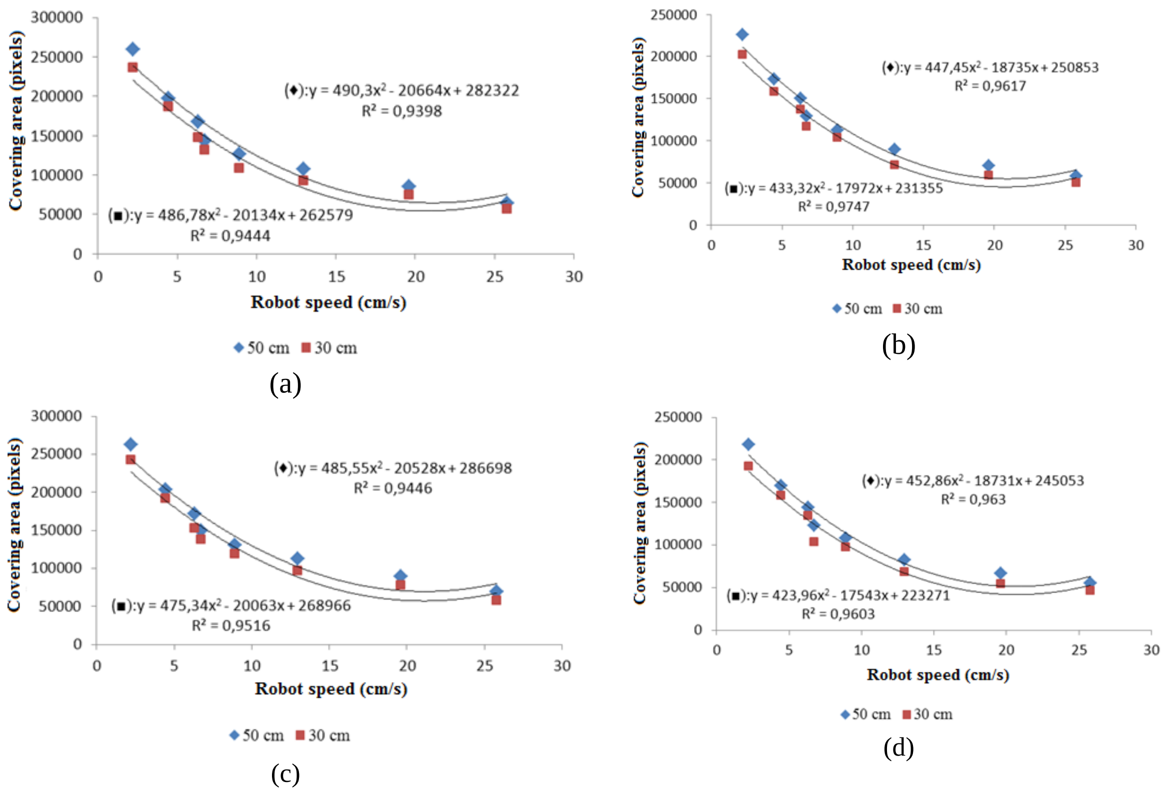


Figure 8. The change of coverage area (pixels) depending on the speed for different weeds: (a) Lamb's quarters; (b) Musk thistle; (c) Prickly lettuce, and (d) Cockspur grass.

(Figure 8).

When nozzle height of spraying robot was 30 and 50 cm, tests for the robot were carried out for 8 different speeds (2.232, 4.469, 6.329, 6.711, 8.928, 12.944, 19.607, 25.806 cm s^{-1}) and covering areas of spraying liquid on surface of weeds was evaluated by using two different methods. In these tests, it was determined that covering areas of spraying liquid on surface of weeds was at the highest when the speed of spraying robot was 2.232 cm s^{-1} and nozzle height was 50 cm above the ground.

DISCUSSION

In the study about precision agriculture, the weeds on sugar beet fields were detected using image processing techniques and a model for variable level spraying liquid application was actualized. The results of this study can be summarized as follows.

With the developed system, the spraying liquid will be applied only to the detected plants instead of the whole field, thus humans, animals, and environmental health will be protected.

The values of inky water applied on the weeds decreased when the speed of smart spraying robot increased. When the speed of smart spraying robot increased from 4.469 to 6.711 cm s^{-1}, a 50% increase, the covering area of spraying liquid for weeds decreased by 10.51%.

The values of spraying liquid applied on the weeds decreased when the speed of smart spraying robot increased. When the speed of smart spraying robot increased from 8.928 to 12.944 cm s^{-1}, i.e. a 44.98% increase, the spraying liquid covering pixel area of weeds decreased by 18.09%.

When the spraying nozzle height of smart spraying robot decreased from 50 to 30 cm, i.e. a %40 decrease, there was a 12.18% decrease in spraying liquid applied to weeds and a 16.70% decrease in spraying liquid pixel area.

The herbicide used on the weeds at sugar beet fields was also spread on to the cultivated plant and this caused residues on the plant. Also, excessive herbicide usage causes not only soil pollution but also pollution of water resources. Because the herbicide will be applied only to the weeds at sugar beet field, no residues will be left. Thus, human and animal health as well as natural environment will be protected.

This robot moves on a rail with its 4 wheels with the aid of an engine. It is designed to be suitable for laboratory conditions. There are self-propelled robot works in the literature. However, tests will be made again by developing the system in our further studies to work more efficiently and regularly in the field conditions and by adapting this system to the tractor three-point linkage system.

By developing the smart spraying system model, variable level herbicide application can be achieved at sugar beet fields. The same system can be used on plants grown in greenhouses and for fluid fertilizer application. This way, the input cost will be lessened.

The system can be mechanically developed and used for hoeing at sugar beet fields. Additionally, it can be used to detect weeds at other cultivated plant fields.

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سامانه رباتیکی هوشمند برای مبارزه با علف هرز چغندر قند

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چکیده

در مزرعه چغندر قند، علف های هرز نه تنها باعث کاهش عملکرد و کیفیت محصول می شوند بلکه هزینه کارگری و تلفات محصول را بالا می برند. در سال های اخیر ، به منظور ازمیان بردن یا کاهش صدمات ناشی از علف های هرز در کشت چغندر قند، مبارزه با علف هرز اهمیت یافته است. به این منظور، پژوهش های متنوعی روی مبارزه با علف هرز با استفاده از روبات ها برای تشخیص علف ها با استفاده ازالگوریتم های پردازش تصویر و مبارزه مکانیکی با کج بیل یا سمپاشی اجرا شده اند. در پژوهش حاضر،علف های هرز مزرعه چغندر قند با استفاده از الگوریتم پردازش تصویر شناسایی شده و ماده ای مایع روی آن ها پاشیده شد..هنگامی که ارتفاع افشانک (nozzle) در۳۰ و ۵۰ سانتی متری زمین بود اندازه گیری های روبات سمپاش در ۸ سرعت انجام شد و سطح پوشید شده با این مایع روی علف با دو روش برآورد شد. نتایج نشان داد که در۴ علف هرز، کاهش ۴۰ درصدی ارتفاع افشانک ربات سمپاش هوشمند به حدودا ۱۲/۱۸٪ کاهش درمساحت سطح پوشید شده با این مایع (بر حسب سانتی متر مربع) منجر شد و این کاهش مساحت بر حسب پیکسل (pixel) ۱۶/۷٪ بود.