Automated detection and control of volunteer potato plants

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Preface

Accomplishing a PhD research project demands a lot of discipline to get all the things done. After five years of collaboration with many people, this thesis is the result of my PhD research project at the Farm Technology Group of Wageningen University.

Much of the work in this thesis was not possible without the help of other people. At the start of the project Joachim Müller and Jan Willem Hofstee motivated me to start working on the methodical design of volunteer potato control, as some grants were available from the Masterplan Phytophtora. Jan Willem, together we succeeded in getting a major grant from the Dutch Technology Foundation STW, which was very beneficial for the success and prolongation of the project. In the meantime, Eldert van Henten started as my promotor, and supported us in the research and writing process.
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June 2009

Contents

Account

The Chapters 2, 3, 4, 5, 6, 7, and 8 have been published or submitted as articles as mentioned on the opening pages of these chapters. Reference should be made to the original article(s). Except for the different font and for changes necessary to add chapter based numbering, the text of the manuscripts was integrally adopted and maintained throughout this thesis.

Chapter 1

Introduction

1.1 Introduction

In this thesis the development of an automated system for volunteer potato detection and control within sugar beet fields is described. This chapter starts with a review of the scope and motivation, and then the problem statement is given. After defining the problem, an overview of a systematic design approach is given, that was used to structure and organize the research. From the systematic design approach the research questions were derived. Finally, the structure of the thesis is listed and gives the roadmap for answering the research questions.

1.2 Scope and motivation

Between 1860 and 2000 an enormous production increase from 10 to more than 40 ton ha^{-1} of ware potatoes was achieved (Vos, 1992). This was called the “production wave” (Bouma & Hartemink, 2002) in agriculture. Then the “environmental wave” followed, that resulted in research that focused on a reduction of fertilizer and chemical inputs in potato cropping (Struik, 2006). That research resulted in a decrease in herbicide use in potato growing. Current research directions support the “societal wave” focusing on consumer friendly and utilization driven research. This resulted in research initiatives that focused on the reduction of fungicide usage in potato cropping as well (Struik, 2006). This demand driven research initiated the Dutch project for volunteer potato plant removal, as farmers’ organizations and researchers together identified volunteer potato plants as sources of spread of ***Phytophthora infestans*** (Schepers ***et al.***, 2000). But, not only in The Netherlands, also in Belgium (Bravo ***et al.***, 2005) and United Kingdom (Tillett & Hague, 2009) projects were initiated for volunteer potato control.

Potatoes are – financially – one of the most important field crops in the Netherlands. They are grown on a total area of 152,000 ha (CBS, 2009). Unfortunately, they are vulnerable to disease, especially to the outbreak of late blight caused by ***Phytophthora infestans***. Late blight is one of the most important potato diseases that is spread, for instance, by volunteer potatoes. These volunteer potatoes originate from tubers that remain in the soil after harvesting. Despite improved harvesting practices, including clod and tuber crushers (Roosjen, 1991) and improved tillage after harvesting, still viable tubers remain in the soil. Volunteer potatoes are potato plants that have survived the winter due to lack of frost. They can be responsible for infesting up to 80,000 plants/ha during the following year after crop rotation has taken place. In this way, volunteer potatoes spread pests and disease to regular potato crops in neighboring fields (Turkensteen ***et al.***, 2000; Boydston, 2001). In the Netherlands, farmers are under the statutory obligation to remove volunteer potato plants from their fields by the 1st of July to a maximum level of two remaining plants per m^2. However, at present, no selective chemicals are available to eliminate the potato tuber or volunteer potato plants within sugar beet fields (Boydston, 2001). Application of glyphosate on volunteer potato plants is very effective, not only for control of the potato haulm, but also for control of the tubers in the soil (Lutman &

Richardson, 1978; Masiunas & Weller, 1988). However, undesired drift from application of glyphosate can cause severe crop damage (Roider ***et al.***, 2007). Therefore several specific glyphosate application mechanisms have been applied in praxis to overcome crop damage due to unwanted glyphosate application to crop plants. Most common are manual or band spray and roller application (Zande & Rops, 1994; Womac ***et al.***, 2004) where only parts of the field are treated with glyphosate. Drawbacks of manual application are the high labor inputs and its related economic consequences for weed control. Drawbacks of band sprayers or glyphosate rollers, that exploit height differences between the weed and crop plant, are that they both do not completely control volunteer plants in the field. Therefore, the remaining plants have to be removed by manually applying glyphosate to the volunteer plants in the field. However, manually removing volunteer plants with up to 30 h/ha labor requirement is too time consuming and therefore too costly (Paauw & Molendijk, 2000). So, there is a definite need for methods to detect and selectively remove volunteer potato plants, both from an economic and environmental perspective.

1.3 Research objective

The main objective was "to develop an automated detection and control system for volunteer potato plants in sugar beet fields". This led to the following question related to the main objective: What are the requirements for automated detection and control of volunteer potato plants in sugar beet fields?

1.4 Design and program of requirements

At the start of the research a systematic design method was applied to unravel the problem of automated detection and control of volunteer plants. Different abstraction levels are distinguished within the systematic design phases. Before starting the design phases, the objective and purpose of the research are defined. At first, the problem definition phase is processed, which results in a function structure. Then, the alternatives definition phase is processed, which results in a concept solution. Finally, in the construction phase a proof of principle or a prototype is made (Roth, 1981; Pahl ***et al.***, 1996; Kroonenberg & Siers, 1998). The three phases of the design process were iteratively applied. This ensured that many alternatives were weighed against each other and that controversial innovative ideas got introduced into the machine design (Wallace & Burgess, 1995). Systematic design approaches have been applied to improve research and development processes within companies, for example to design better mechatronics systems (Salminen & Verho, 1992). Furthermore, the design approach assists in unraveling complex systems with limited budget and time. This systematic design method has been previously applied to design for example an autonomous weeding robot (Bakker ***et al.***, 2004) and a greenhouse control system (Speetjens ***et al.***, 2008). These were both systems that included many functions where electronic hardware and software had to be combined, in a way similar to the research in this thesis.

1.5 Problem definition phase

The purpose and objective of the system is to control the volunteer plants within sugar beet fields. During the problem definition phase a program of requirements was set. This program was defined in collaboration with commercial companies and end-users of the system; arable farmers that grow potatoes and sugar beets. After a few iterations of the design phases, this resulted in the following list of requirements for the integrated system:

- resolution of detection at least 2×2 mm (4 mm^2),
- work under variable natural light conditions,
- resolution of control at least at 10×10 mm (100 mm^2),
- glyphosate application targeted on volunteer plants only,
- driving speed up to 2 m s^{-1},
- control of volunteer plants > 95 %,
- undesired control of sugar beet plants < 5 %,
- working width between 15-23 cm; within the sugar beet crop seed line,
- modular system, applicable on a multiple of three rows of sugar beet plants,
- machine has to work attached to a tractor,
- integration with existing mechanical weeders as an add-on would be preferred.

After the problem definition phase, the functions were defined. Five functions were defined to unravel the problem of automatic detection and control of volunteer potato plants. First, a coarse localization of volunteer potato plants within a field is required to identify where a control action should be taken. Then, the system has to move to the plants within the field. Third, a detailed weed plant detection system detects where volunteer plants are positioned. The fourth function is to move the actuator above or near the volunteer potato plant. Finally, the potato plant inclusive the tubers has to be controlled.

1.6 Alternatives definition phase

In the alternatives definition phase, no restrictions apply to the proposed methods that fulfill a function. Alternative methods were generated based on a literature review and brainstorm sessions. The methods for detection and control of weeds retrieved from literature – not intended to be complete – is explained in the following paragraphs. Then, some of the proposed methods are shown in the morphological chart, Figure 1.1.

Automatic weed detection and control systems were subject of research in the past. For example weeds were controlled within the seed line of tomato plants by Lee ***et al.*** (1999). They applied a vision system and a micro-sprayer to apply herbicides on the weeds. In Belgium, a vision based patch sprayer was developed that controlled volunteer potato plants in sugar beet fields (Bravo ***et al.***, 2005). Image processing has been used extensively to discriminate between species.

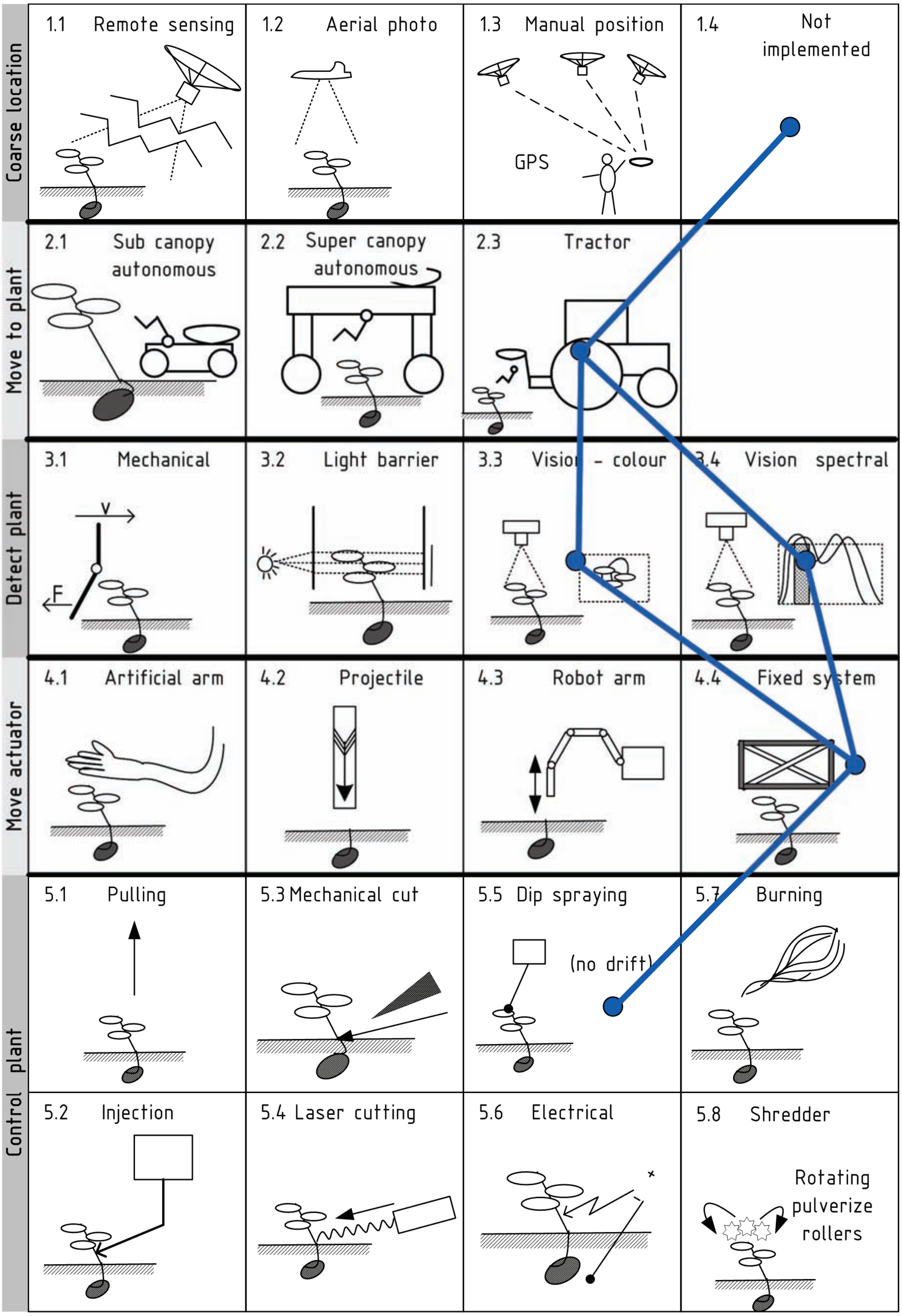

Figure 1.1 Part of the morphologic chart. The five functions are shown in the leftmost column. Possible methods to fulfill a function are shown with a pictogram. From the methods a combination was chosen as a structure indicated with the line.

After soil background subtraction, plant objects were classified based on shape, colour and texture (Guyer ***et al.***, 1986; Woebbecke ***et al.***, 1995; Gerhards & Christensen, 2003). Compared to shape and texture-based detection, colour based detection algorithms are faster and less complex (Perez ***et al.***, 2000). Occluding and twisting leaves negatively affect the consistency of shape, colour, and texture parameters. In addition, the colour based detection systems have to challenge the variability of natural light conditions during various crop growth stages between April and July.

Multispectral analysis of crop and weed reflections, to some extent, already deal with some restrictions of image processing, for example, occluded leaves and inconsistent shape features (Vrindts ***et al.***, 2002). In addition, multispectral measurements give information outside the visible spectrum that traditional digital cameras can measure. For example, Thenkabail ***et al.*** (2000) took multispectral measurements from several crop species in different growth stages. However, sugar beets, our crop species of interest, was not measured. Thenkabail ***et al.*** (2000) indicated that narrow band ranges are suitable for discrimination between crops.

For control of volunteer potato plants, haulm removal is not enough to control the complete plants including tubers (Williams & Boydston, 2002). Another option would be to pull the plants out of the soil, however this did not give promising results in preliminary research as in many cases the tubers remained in the soil and were deeply buried. Like the research on weed control in tomato plants from Lee ***et al.*** (1999), in Denmark research was done on a weed seedling micro-sprayer by Graglia (2004) and Sogaard & Lund (2007). The weed plant specific application of glyphosate minimizes the risk of unwanted spray deposit onto crop plants as well. However, the viscosity of the spray fluid has to be changed compared to traditional flat fan spraying because of splashing and micro-drift effects (Downey ***et al.***, 2004). When viscosity and surface tension are changed, the efficacy of the spray is unknown and is expected to change as well (Ennis & Williamson, 1963; Douglas, 1968). In addition to this, to our best knowledge, no research was done on the efficacy of different droplet spread patterns when they are applied with micro-sprayers.

Combinations of methods were rated, which resulted in a structure. In the structure that was chosen, the following solutions for functions were proposed. Coarse location was not implemented, as this was not important at this stage of the research. Entire fields have to be treated because of the random nature of appearance of volunteer potato plants. In preliminary research, positions of volunteer plants were measured in the field with GPS. It appeared that the distribution of the plants was random throughout the fields.

The second function, move to plant, was implemented with a human operated tractor. The development of autonomous vehicles and the navigation through the field was not a part of this research.

Then, in this concept structure, the plants were detected with a combination of color based machine vision detection and machine vision spectral detection. Based on the results that were achieved in the past and reported in literature, these methods showed high potential. However, the spectral reflectance of volunteer potato plants and sugar beet plants has not been investigated and combined with machine vision for detection of those weed plants. So, this has to be explored in this research in a way that detection can be realized in real time behind a tractor under field conditions where plants have varying properties.

For the fourth function, move actuator, a fixed system was preferred. This reduces the construction complexity and possible breakdowns in an agricultural environment. Control of the plants is achieved with dip spraying. This is a method that applies glyphosate in a novel way with larger targeted droplets without any spray drift. However, the performance for control of larger weeds with a drop-on-demand sprayer is still unknown. Therefore, dose-response studies are required to determine the required amount and functioning of such a sprayer.

1.7 Constructing phase

Once alternatives were weighed and a structure was chosen, a machine was constructed. The machine was connected to the three point linkage of a tractor. With this machine measurements could be done in the field, to determine the precision of detection and the efficacy of spraying. It facilitated measurements in the field and the gathering of data to answer the following research questions.

1.8 Research questions

Based on the previous analysis and concept structure, the following research questions were derived.

1. What reflectance properties can be used for detection of volunteer potato plants?
2. Which methods are best suited to classify image pixels?
3. What is the improvement of á priori information in an adaptive classification algorithm?
4. How to implement the algorithms in a real-time system?
5. What is the dose-response of tuber yield and photosynthesis activity of volunteer potato plants to glyphosate?
6. What are the perspectives in using a micro-sprayer for volunteer potato control?
7. What is the integrated system performance?

1.9 Thesis outline

In Chapter 2 the reflection properties of sugar beet and volunteer potato plants are described and research question 1 is addressed. Multispectral narrow-band measurements in the range of 450 to 1650 nm were done on multiple growth stages, in two fields, and repeated in 2006 and

2007. Wavebands in the visible and near-infrared range that discriminate between sugar beets and volunteer potato plants were identified.
Chapter 3 describes the broad-band colour based detection of volunteer potato plants in sugar beet fields with machine vision techniques. A neural network and multivariate classifier approach were assessed for their ability to discriminate between the crop and weed, to answer research question 2.

In Chapter 4, the detection of volunteer potato plants under variable outdoor conditions is assessed. The classification accuracy under changing natural light conditions is compared with constant natural light conditions. Even under constant conditions, crop and weed discriminative properties change within a field, subsequently adaptive algorithms were needed for classification and question 3 was addressed.

Chapter 5 elaborates on the detection of volunteer potato plants under controlled conditions. Now the measurement setup was covered and controlled light was applied for the detection. Visible light and near-infrared light images were used to discriminate. An adaptive self learning algorithm was developed and tested. The computer algorithm was now implemented in a real-time operating system to work deterministically in field conditions and the focus was on research question 4.

Chapter 6 gives the relation between volunteer potato plants and the herbicide glyphosate that is applied for control of volunteer plants, as was stated in question 5. Glyphosate was applied in three growth stages with flat fan nozzles and different concentrations. In Chapter 7, the dose effect study is extended for micro-sprayer applied glyphosate onto volunteer plants. Furthermore, question 6 was addressed and the perspectives of the micro-sprayer were evaluated.

Chapter 8 evaluates the integrated detection and control system for volunteer potato plants. The efficacy under field conditions and the precision of spraying was evaluated, to answer question 7.

The implications for arable farming weed control practices are given in the final chapter. This final chapter includes a general discussion and conclusions in relation to the objectives of the research.

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Chapter 2

Classification of sugar beet and volunteer potato reflection spectra with a neural network and statistical discriminant analysis to select discriminative wavelengths

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2.1 Abstract

The objectives of this study were to determine the reflectance properties of volunteer potato and sugar beet and to assess the potential of separating sugar beet and volunteer potato at different fields and in different years, using spectral reflectance characteristics. With the ImspectorMobile, vegetation reflection spectra were successfully repeatedly gathered in two fields, on seven days in two years that resulted in 15 datasets. Both in the visual and in the near-infrared reflection region, combinations of wavelengths were responsible for discrimination between sugar beet and volunteer potato plants. Two feature selection methods, discriminant analysis (DA) and neural network (NN), succeeded in selecting sets of discriminative wavebands, both for the range of 450-900 nm (sensor 1) and 900-1650 nm (sensor 2). First, 10 optimal wavebands were selected for each of the 15 available datasets individually. Second, by calculating the discriminative power of each selected waveband, 10 fixed wavebands were selected for all 15 datasets analyses. Third, 3 fixed wavebands were determined for all 15 datasets. These three wavebands were chosen because these had been selected by both DA and NN and were for sensor 1: 450, 765, and 855 nm and for sensor 2: 900, 1440, and 1530 nm. With the resulting three sets of wavebands, classifications were performed with a DA, a neural network with 1 hidden neuron (NN1) and a neural network with two hidden neurons (NN2). The maximum classification performance was obtained with the "10 optimal" waveband set, where the percentages were 100±0.1% and 1±1.3% for True Negative (TN) classified volunteer potato plants and False Negative (FN) classified sugar beet plants respectively for the average of 5 sand plots. This was for the NN2 method and sensor 2. In general the NN2 method gave the best classification results, followed by DA and finally the NN1 method. When the 15 "10 optimal" waveband sets were generalized to a set of "10 fixed" wavebands, the classification results were still at a reasonable level of a performance at 87% TN and 1% FN for the NN2 classification method. However, when a further reduction and generalization was made to "3 fixed" wavebands, the classification results were poor with a minimum performance of 69% TN and 3% FN for the NN2 classification method. So, these results indicate that for the best classification results it is required that the sensor and classification system adapt to the specific field situation, to optimally discriminate between volunteer potato and sugar beet pixel spectra.

Keywords: weed, detection, discriminant analysis, neural network, sensors, analysis, intelligence

2.2 Introduction

Volunteer potato plants are an important weed in sugar beet crops in the Netherlands. As a consequence, much attention is paid to the control of these weeds. Plants sprouting from overwintered tubers are difficult to control in sugar beet, where no selective herbicides are available. Left uncontrolled, volunteer potato harbours diseases like late blight (*Phytophthora infestans*), insects, and nematode pests of potato. As a result, the positive effects of crop rotation are lost (Boydston, 2001).

Sugar beet is a common rotational crop with potato in the Netherlands. The sugar beet crop grows in rows which gives farmers better opportunities to control the volunteer potatoes with glyphosate. The space between the rows is treated mechanically or with band sprayers while the volunteer potato plants growing within the rows have to be treated manually. This task is labour intensive – up to 30 hours per ha (Paauw & Molendijk, 2000) – and automation is required to give farmers economically attractive opportunities for volunteer potato control.

The initial step in automation of volunteer potato removal is their detection. In the present study we design methods for volunteer potato detection within the sugar beet crop rows using the reflective properties of the crops and the volunteer potato weed. Commercially available systems, e.g. WeedSeeker (Ntech Industries Inc., Ukiah, CA, USA), distinguish green plant material from the soil and other background elements and spray only where plant material is present. However, in addition to the discrimination of green plant material and background, inter-species discrimination is necessary for volunteer potato control within a sugar beet crop. Previous researchers have used image processing to discriminate between species. After soil background subtraction, plant objects were classified based on shape, colour, and texture (Guyer *et al.*, 1986; Woebbecke *et al.*, 1995; Gerhards & Christensen, 2003; Nieuwenhuizen *et al.*, 2007). Nevertheless, this classification process still has several problems that require a solution. For example, the changing light conditions strongly influence the classification success. Occluding and twisting leaves also negatively affect the consistency of shape, colour, and texture parameters. Multispectral analysis of crop and weed reflections, to some extent, already deal with some restrictions of image processing, for example, occluded leaves and inconsistent shape features (Vrindts *et al.*, 2002), due to the per pixel classification of spectral reflection. In addition, multispectral measurements give information outside the visible spectrum that traditional digital cameras can measure. For example, Thenkabail *et al.* (2000) took multispectral measurements from several crop species in different growth stages. However, sugar beets, our crop species of interest, was not measured. Thenkabail *et al.* (2000) indicated that narrow band ranges are suitable for discrimination between crops. Nevertheless, the influences of changing crop growth stage conditions in the field are rarely taken into account when taking experiments for crop/weed identification systems. Most other studies did not repeatedly measure different growth stages, neither measured different fields with different soil types and years to find consistent discriminative wavelength bands.

The objectives of this study were to determine the reflectance properties of volunteer potato and sugar beet and to compare the ability of various sensor and algorithm combinations to separate sugar beet and volunteer potato at different measurement days, different soils, and different years, using spectral reflectance characteristics. The scope of the research covers spectra in both the visible and the near infra-red range gathered in two different fields with two different soil types and different crop varieties. The spectra were gathered in 2006 and 2007. The influences of different fields and crops on characteristic wavelength reflection were investigated with neural network and statistical stepwise discriminant analysis wavelength selection methods.

2.3 Material and methods

Multispectral recordings of five sugar beet and five volunteer potato plants were taken in 2006 and 2007 at three different growth stages and in two fields. The recordings registered vegetation reflection at 167 wavelength bands between 450 and 1665 nm and a minimum of 100 spectra were recorded for each plant that was measured.

1) In-field data recording

On May 17, June 2, and June 20, 2006, spectral measurements were taken on two fields in Wageningen, The Netherlands. On May 15, May 29, June 12, and June 19, 2007, again measurements were taken on two fields in Wageningen, The Netherlands. The first field had a clay soil and the second field had a sand soil. In both fields, sugar beet and volunteer potato plants were present. Due to crop rotation, the identical fields could not be used in 2007, but they were within 500 m of each other and of the same soil type. The number of plants measured is given in Table 2.1. At some dates, data was not recorded due to non-emerged plants or missing plants as a result of weed control practices on the farm.

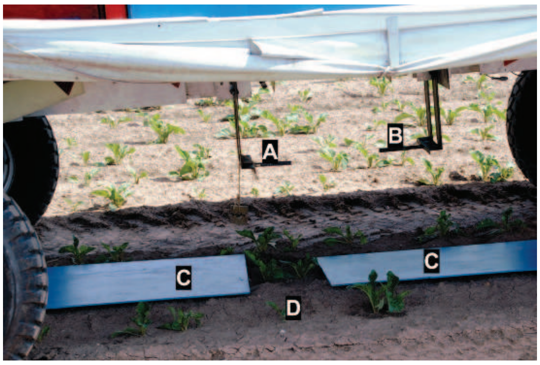

Figure 2.1 ImspectorMobile measurements in a sugar beet field. A and B are reflectance references in the field of view of sensor 1 and sensor 2 respectively. C are plastic sheets covering vegetation that was not recorded. D is one of the plants recorded by sensor 1.

The ImspectorMobile (Molema *et al.*, 2003) vehicle was used to take measurements of sugar beet plants and volunteer potato plants in each field as shown in Figure 2.1. The plants were randomly chosen in the field and marked, such that they could be traced on the successive measurement days. Measurements on clay soil were delayed in 2007, due to a later crop emergence on the fields. To ensure that only sugar beet or volunteer potato reflections were measured, the area before and after the plant was covered with blue plastic sheets as shown in Figure 2.1. Xenon flash lights (Broncolor, Bron Elektronik Ltd., Allschwil, Switzerland) and adequate shielding to prevent sunlight influence were used to maintain constant lighting conditions. Furthermore, a 50% reflectance reference panel (Spectralon®, Labsphere, North Sutton, NH, USA) was measured in each recording to standardise the measured reflectance. Depending on the actual growth stage, between 20 and 30 line spectra were recorded from each plant. Recordings from 450 to 900 nm were done with sensor 1 that consisted of a spectrograph (V9 Imspector, Specim, Oulu, Finland) and a camera (Kappa DX2HC, Gleichen, Germany). Recordings from 900 to 1650 nm were done with sensor 2 that consisted of a spectrograph (N17 Imspector, Specim, Oulu, Finland) and a camera (AlphaNir Indigo, FLIR, Goleta, CA, USA).

A slit of 80 micron was used within both spectrographs. Due to the slit width, sensor 1 and sensor 2 produced 91 and 75 wavelength bands of 5 nm and 10 nm bandwidth respectively. Both sensors had a field of view of 1.2 mm by 12 cm and the height above the ground was 50 cm. So, the spatial resolution of the spectral measurements was 1 mm^2. The driving velocity was approximately 1 cm s^{-1} and images were recorded every cm in the travel direction. The data from sensor 1 and sensor 2 were separately analysed as they were measured independently in the field (see Figure 2.1). For sensor 1, soil spectra were removed from the dataset based on the following equations:

$$\text{Pixel is plant if}: \frac{R_{680}}{R_{743}} < 0.5 \text{ and } \frac{R_{555}}{R_{680}} > 1.0 \text{ and } R_{680} < 0.15 \text{ and } NDVI \geq 330$$

where R_{743} is the interpolated reflectance between R_{740} and R_{745} and $NDVI = 1024 \times \frac{R_{750} - R_{675}}{R_{750} + R_{675}}$.

For sensor 2, the following equation was used:

$$\text{Pixel is plant if}: \frac{R_{1456}}{R_{1130}} < 0.7 \text{ and } R_{1456} < 0.3$$

where R_{1456} is the interpolated reflectance between R_{1450} and R_{1460}. The thresholds were based on examining data of multiple experiments.

Table 2.1: Overview of measurements in 2006 and 2007. The recording dates, soil types, number of sugar beet and potato plants recorded, and the number of spectra recorded for two sensors are listed. On some dates plants were not available (n.a.) in the field.

					Sensor 1		Sensor 2	
Recording date	Soil type	Sugar beet plants	Potato plants	Data set #	Sugar beet spectra	Potato plant spectra	Sugar beet spectra	Potato plant spectra
17-5-2006	clay	5	5	1	179	779	228	1510
	sand	5	5	2	426	1690	1003	569
	clay+sand	10	10	3	605	2469	1231	2079
2-6-2006	clay	5	3	4	744	263	2213	971
	sand	5	4	5	4260	115	4720	265
	clay+sand	10	7	6	5004	372	6933	1236
20-6-2006	clay	5	4	7	17597	4922	4268	4267
	sand	*n.a.*	*n.a.*	-	*n.a.*	*n.a.*	*n.a.*	*n.a.*
	clay+sand	*n.a.*	*n.a.*	-	*n.a.*	*n.a.*	*n.a.*	*n.a.*
15-5-2007	clay	*n.a.*	*n.a.*	-	*n.a.*	*n.a.*	*n.a.*	*n.a.*
	sand	5	5	8	343	1475	91	218
	clay+sand	*n.a.*	*n.a.*	-	*n.a.*	*n.a.*	*n.a.*	*n.a.*
29-5-2007	clay	5	5	9	960	6795	599	1433
	sand	5	5	10	1859	5938	390	2130
	clay+sand	10	10	11	2819	12732	989	3563
12-6-2007	clay	5	5	12	546	1376	3208	1151
	sand	5	5	13	0	414	1454	198
	clay+sand	10	10	14	546	1790	4662	1349
19-6-2007	clay	5	5	15	932	3112	6374	5830
	sand	*n.a.*	*n.a.*	-	*n.a.*	*n.a.*	*n.a.*	*n.a.*
	clay+sand	*n.a.*	*n.a.*	-	*n.a.*	*n.a.*	*n.a.*	*n.a.*

Fifteen datasets (Table 2.1) were available for analysis. The image pixels were identified as sugar beet and volunteer potato using variable selection methods followed by a classification. Variable selection methods were preferred as for future detection systems specific discriminating wavelengths are required. The available spectra were used for selection and classification as follows: fifty percent of the dataset was used for selection of variables and fifty percent was used for classification and verification of the methodology.

2) Statistical discriminant analysis selection method (DA)

Ten wavebands were selected with the SAS STEPDISC forward selection procedure. The waveband that was the best discriminator among the available, not yet selected wavebands, was added to the set of selected wavebands. The addition of discriminating wavebands was stopped when ten wavebands were selected. This procedure was done for the fifteen available datasets, and resulted in a ranked list of ten selected discriminative wavelengths for each of these datasets.

3) Neural network selection method (NN)

To overcome the restrictions of only investigating linear relationships with statistical discriminant analysis as variable selection method, a neural network wavelength selection method was used as well. A fully connected Kohonen neural network with three layers was trained and used for classification (Meuleman, 1998). The input layer consisted of the reflection variables, the hidden layer consisted of one hidden neuron, and the output layer consisted of two neurons, one for the volunteer potato class and one for the sugar beet class. Each neuron in the hidden layer and in the output layer was first thresholded, then the transfer function was applied. The transfer functions in the neural network were unipolar sigmoid functions of the form: $y = \frac{1}{1+e^{-x}}$. A forward inclusion method of input variables was used. More specifically, the first waveband that was included separated the two output classes the best with a net including one input variable. Each next step the net was expanded with one input variable. Then, a waveband was included that separated the two output classes better compared to the remaining wavebands. The inclusion of wavebands was stopped when no decrease in remaining variance was seen. A conjugate gradient algorithm was used to calculate optimal weights within the net. To prevent the conjugate gradient method from getting stuck in local minima, the training procedure of the net was restarted 50 times with randomly chosen weights.

After the selection procedure, a leave-one-out analysis was done to determine the relative importance of the selected wavelengths. This was required as the neural network topology changed each step when a waveband was added, as additional degrees of freedom were created by adding weights required for the new input variables. To determine the relative importance of the first ten selected wavebands as described in the previous procedure, the neural network topology was fixed with nine input variables. Then, the first ten selected wavelength bands were inserted into the neural network at once, except one waveband. This was repeated ten times for a different wavelength band that was left out. In this way, a leave-one-out test was done to determine the variation that was explained by the ten individual wavelengths. In this leave-one-out test the neural network was restarted 150 times to prevent the conjugate gradient method from stopping in local minima. With this leave-one-out test the 10 most important wavelengths within the set of selected wavelengths could be determined and ordered.

4) Discriminative power for selection of wavebands

To summarize the results of the stepwise discriminant selection and neural network wavelength selection procedure over the soil-types and over all datasets, the following equation was used to determine the discriminative power of a selected waveband (*w*):

$$\text{Normalized discriminative power}\ (w) = \frac{\sum_{1}^{N} \text{rankpoint}_{w}}{\text{Total rank points}} \tag{2.1}$$

where N is the total number of datasets over which the power is determined, rank_w is the rank of the wavelength band in the list of selected wavebands. A higher ranking waveband explained more variance in that specific dataset. The highest ranking wavelength band received 10 points, the lowest ranking wavelength band received 1 point. The sum of the rank points was divided by the total rank points given for the N datasets which yielded the normalized discriminative power of the wavelength band *w* as a result. So, Equation 2.1 facilitated a summarized ranked lists of wavebands for a group of datasets. These lists were made for the clay soil (N=6), for the sand soil (N=5), for the clay + sand soil (N=4), and for all the datasets (N=15). The lists were analyzed for differences in selected wavebands.

5) Classification

Once the discriminative wavebands had been selected, the classification performance was determined. This was done for three sets of wavebands.

1) For the “10 optimal” wavebands that were selected for each individual dataset with both selection methods, yielding 60 sets of 10 optimal wavebands (15 datasets × 2 sensors × 2 methods) .
2) For a set of “10 fixed” wavebands that were selected from the previously described 60 sets of optimal wavelengths, yielding 4 sets of 10 fixed wavebands (2 sensors × 2 methods) .
3) For a set of “3 fixed” wavebands that were selected by both the DA and the NN from the 60 sets of optimal wavelengths, yielding 2 sets of 3 fixed wavebands (2 sensors = 2 sets).

The three sets of wavebands were used for three methods of classification, 1) a statistical discriminant analysis (DA), 2) a neural network with 1 hidden neuron (NN_1), and 3) a neural network with 2 hidden neurons (NN_2).

The statistical discriminant analysis consisted of a discriminant rule that was made in the SAS DISCRIM procedure. The DISCRIM procedure is based on Bayes’ theorem for multivariate classification. Individual within-group covariance matrices were used, that resulted in a quadratic discriminant rule. The discriminant rule is based on the Mahalonobis distance to the group means of the 15 training datasets. The classification with the derived discriminant rule was done on the 15 classification datasets.

The neural network was trained on the 15 training datasets to set the weights correctly in the neural net. Then the pixels of the 15 classification datasets were classified. A neural network with 2 hidden neurons was added to the first two methods, as this network could probably better fit the variability in the data, especially for the set of 3 fixed wavelengths. This would then result in better classification.

6) Classification performance measures

The quality of classification on the second half of the dataset was determined with confusion tables as defined in Table 2.2.

Table 2.2 Definition of the confusion table for classification of volunteer potato (VP) and sugar beet (SB) pixel reflections based on the spectral measurements.

		Classification		
		VP	SB	Sum
Ground truth	VP	True negative (TN)	False positive (FP)	100%
	SB	False negative (FN)	True positive (TP)	100%

In the ideal situation TN and TP both equal to 100%. Special attention was on the TN and FN percentages as a removal device will act on 'pixels' classified as VP. Therefore the FN percentage is an important performance measure as well.

2.4 Results

Discriminative wavelength selection with DA and NN

The forward inclusion approach for selecting discriminative wavelengths reduced the number of wavelengths. The number of wavebands was reduced from 167 to a maximum of 10 that were needed for > 90% TN and TP classification of the spectra within a dataset. This applied for the DA as well as for the NN. However, for the 15 datasets still 63 and 66 different wavebands out of 91 were selected with the NN and DA for sensor 1. And 56 and 64 different wavebands out of 75 were selected with the NN and DA for sensor 2. This is illustrated in Figure 2.2 that shows the discriminative power of the wavelength bands of the two sensors. The graph shows the "10 optimal" wavelength bands that were selected for each of the 15 processed datasets and one can see that the selected bands are quite evenly distributed over the available wavelengths. So, bands from both the visible as well as from the near-infrared region were needed for discrimination. The largest bubble represents the 1530 nm band that was – always in combination with other bands – one of the most powerful discriminative bands within the discriminant analysis.

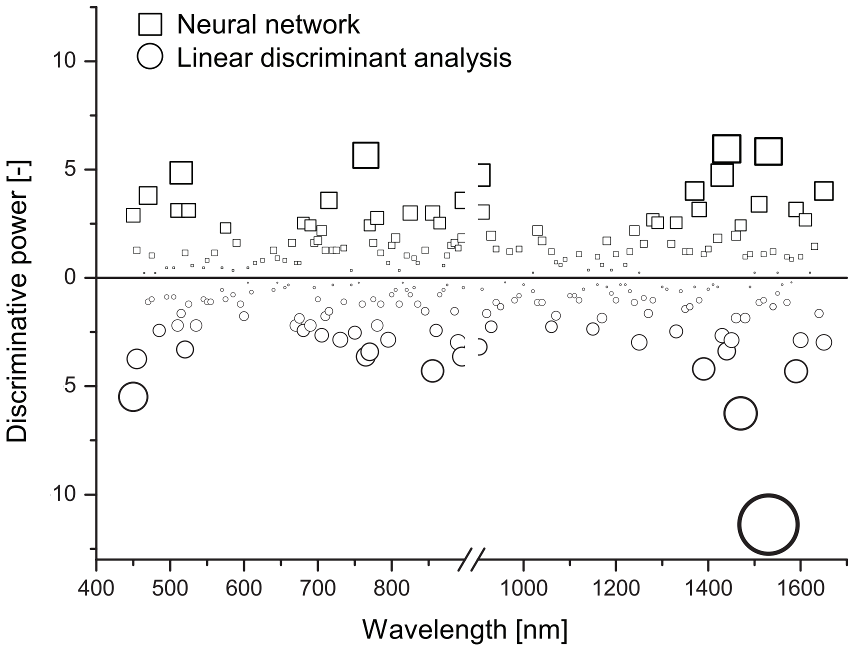

Figure 2.2 The normalized discriminative power between sugar beet and potato reflectance spectra of a specific band is shown as a function of all measured wavelength bands. Larger bubbles and squares indicate larger discriminative power for the linear discriminant analysis and neural network respectively. Results for the “10 optimal” wavebands for the 15 datasets.

The results of the ranking procedure according to Equation 2.1 are summarized in Table 2.3. Columns 3+4 and 5+6 of Table 2.3 show selected wavebands for clay and sand plots. On the clay plot for both sensors five wavebands were selected by both NN and DA. However, the discriminative power was not found identical, as the position of the bands was different in the list. Except the 1530 nm waveband from sensor 2. This band had the highest discriminative power for both selection methods.

On the sand plot, for both sensors three wavebands were selected by both NN and DA. None of the wavebands had a similar ranking in terms of discriminative power. For sensor 1, the set of ten wavebands was completely different for the sand soil compared to the clay soil plot. For sensor 2, 1440 nm, 1530 nm and 1590 nm were selected both on the sand and the clay plot. The third to eight column in Table 2.3 represents the ordered list of selected wavebands for the four days that measurements were done on both clay and sand soil. This resulted in only two and three identical selected wavebands for sensor 1 and 2 respectively. The last two columns list the result of the ranking when the “10 optimal” wavebands for all the 15 datasets were ranked, that resulted in “10 fixed”. In this case, for sensor 1 and 2, three and five bands were found identical, but none of them had a similar ranking in terms of discriminative power.

Table 2.3 Ten most important wavebands after ranking of discriminative power. Wavelengths given for both selection methods, and for both sensors. The results are split for individual soil types and soil types combined. Bands marked with asterisk (*) were found by both methods. Bands marked with crosshatch (#) were found by both methods and were used for further analyses.

	rank list	clay N=6		sand N=5		clay+sand N=4		over-all N=15	
	postion	NN	DA	NN	DA	NN	DA	NN	DA
sensor 1 450-900 nm	1	715	680	525*	450*	515	770*	765*#	450*#
	2	765*	895*	450*	520*	765*	765*	515	855*#
	3	515	455	900	675	470	450	470	455
	4	705	690*	695	855	680	520	715	765*#
	5	510	780*	775	525*	575	730	900	895
	6	855*	855*	865	600	885	890	510	770
	7	825	765*	640	760	770*	455	525	520
	8	895*	795	720	810	805	595	825	890
	9	780*	750	520*	470	845	795	855*#	730
	10	690*	860	560	535	900	895	450*#	795
sensor 2 900-1600 nm	1	1530*	1530*	1370	1530	1030	1530*	1440*#	1530*#
	2	1440*	1390	1510	1330	1530*	1470	1530*#	1470
	3	1650*	1430*	1260	1450	1040	920	900*#	1590*
	4	900	1470	940*	1470*	1510	1460	1430	1390
	5	1430*	1250	1440	1590	900	930*	1370	1440*#
	6	1380	1650*	1460	1170	930*	1070	1650*	900*#
	7	1590*	1440*	1060*	900	1330	1390	1510	1250
	8	1610	1590*	1290	1540	1440*	1200	1380	1650*
	9	910	1600	1470*	1060*	1590	1440*	1590*	1450
	10	1240	1270	1200	940*	970	1260	910	1600

The “10 fixed” wavebands from the last two columns of Table 2.3 and the “3 fixed” wavebands that were found identical by both NN and DA selection are shown in Figure 2.3. The “3 fixed” wavebands were for sensor 1: 450 nm, 765 nm, and 855 nm and for sensor 2: 900 nm, 1440 nm, and 1530 nm, respectively. The positions of the “10 fixed” and “3 fixed” wavebands on a plant pixel reflection spectrum are visualized in Figure 2.3.

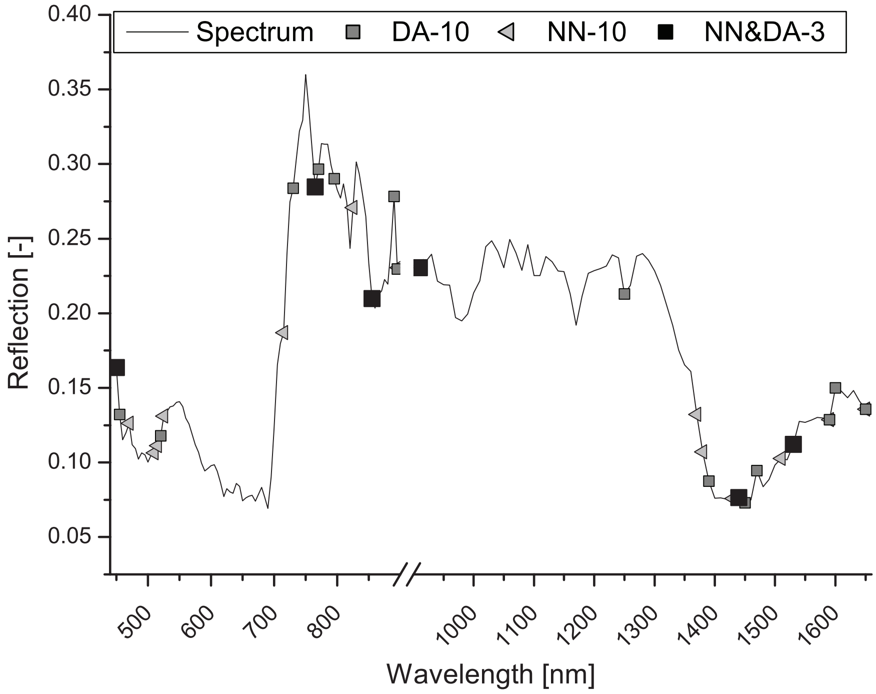

Figure 2.3 Selected discriminative wavelength bands shown on an arbitrary measured spectrum. On the left of the x-axis break the selected bands for sensor 1, on the right the bands for sensor 2. DA-10: 10 fixed wavebands for discriminant analysis selection method, NN-10: 10 fixed wavebands for neural network selection method, NN&DA-3: 3 fixed wavebands that were selected by both the neural network and the discriminant analysis.

Classification performance with 10 optimal, 10 fixed, and 3 fixed bands

The classification performance with the three sets of wavebands and with the three methods of classification (10 optimal, 10 fixed, and 3 fixed) is shown in the confusion tables 2.4, 2.5, and 2.6.

Table 2.4 Confusion tables of the classification results using "10 optimal" wavebands. Ten optimal wavebands were adapted to the variability in each dataset. The average classification percentages and standard deviation are given for each group of n datasets and for sensor 1 (s1) and sensor 2 (s2). The upper third shows the results of the discriminant analysis (DA), the middle part shows the results of the neural network with one hidden neuron (NN1), and the lower third shows the results of the neural network with two hidden neurons (NN2).

DA	clay n=6		sand n=5		clay+sand n=4		overall n=15	
s1	97±3.1	3±3.1	98±1.6	2±1.6	93±9.6	7±9.6	96±5.4	4±5.4
	8±8.7	92±8.7	2±2.0	98±2.0	5±6.0	95±6.0	5±6.6	95±6.6
s2	93±8.0	7±8.0	93±7.0	7±7.0	89±9.2	11±9.2	92±7.6	8±7.6
	5±3.9	95±3.9	2±2.2	98±2.2	3±2.9	97±2.9	3±3.2	97±3.2
NN1	**clay n=6**		**sand n=5**		**clay+sand n=4**		**overall n=15**	
s1	98±2.4	2±2.4	99±1.0	1±1.0	96±5.1	4±5.1	98±3.1	2±3.1
	9±10.0	91±10.0	2±2.2	98±2.2	4±4.6	96±4.6	5±7.3	95±7.3
s2	98±2.5	2±2.5	97±2.7	3±2.7	96±5.6	4±5.6	97±3.4	3±3.4
	6±5.8	94±5.8	2±2.7	98±2.7	4±2.8	96±2.8	4±4.3	96±4.3
NN2	**clay n=6**		**sand n=5**		**clay+sand n=4**		**overall n=15**	
s1	99±1.4	1±1.4	100±0.1	0±0.1	99±0.8	1±0.8	99±1.1	1±1.1
	5±6.2	95±6.2	1±1.3	99±1.3	3±4.7	97±4.7	3±4.7	97±4.7
s2	98±1.8	2±1.8	97±3.3	3±3.3	97±2.9	3±2.9	98±2.5	2±2.5
	3±4.0	97±4.0	1±1.6	99±1.6	2±1.5	98±1.5	2±2.7	98±2.7

Table 2.4 shows that the DA gave between 89% and 98% TN classified volunteer potato (VP) pixel spectra and between 2% and 8% FN classified sugar beet (SB) pixel spectra. The NN with one hidden neuron, NN1, gave between 96% and 99% TN classified VP pixel spectra and between 2% and 9% FN classified SB pixel spectra. The NN with two hidden neurons, NN2, gave between 97% and 100% TN classified VP pixel spectra and between 1% and 5% FN classified SB pixel spectra. NN2 yielded better classification results than NN1 and DA.

The standard deviations shown in the confusion tables were lower for NN2 with a maximum of 6.2% compared to the standard deviations for DA and NN1 with a maximum of 9.6% and 10.0%, respectively. The spectra recorded on the sand soils were better discriminated than the spectra recorded on the clay soils. This resulted in higher TN and lower FN classification percentages on the sand soils.

Table 2.5 Confusion tables of the classification results using "10 fixed" wavebands. Ten optimal wavebands were adapted to the variability in each dataset. The average classification percentages and standard deviation are given for each group of n datasets and for sensor 1 (s1) and sensor 2 (s2). The upper third shows the results of the discriminant analysis (DA), the middle part shows the results of the neural network with one hidden neuron (NN1), and the lower third shows the results of the neural network with two hidden neurons (NN2).

DA	clay n=6		sand n=5		clay+sand n=4		overall n=15	
s1	92±6.9	8±6.9	95±5.0	5±5.0	90±11.1	10±11.1	93±7.4	7±7.4
	9±9.2	91±9.2	5±4.8	95±4.8	7±7.3	93±7.3	7±7.3	93±7.3
s2	91±9.5	9±9.5	85±20.5	15±20.5	87±11.8	13±11.8	88±13.8	12±13.8
	5±4.0	95±4.0	3±3.6	97±3.6	4±3.4	96±3.4	4±3.5	96±3.5

NN1	clay n=6		sand n=5		clay+sand n=4		overall n=15	
s1	93±6.1	7±6.1	97±2.9	3±2.9	94±5.4	6±5.4	95±5.1	5±5.1
	21±27.3	79±27.3	4±4.5	96±4.5	12±12.5	88±12.5	13±19.1	87±19.1
s2	92±7.8	8±7.8	72±42.6	28±42.6	85±16.3	15±16.3	83±26.1	17±26.1
	6±6.1	94±6.1	1±2.7	99±2.7	3±4.6	97±4.6	4±4.9	96±4.9

NN2	clay n=6		sand n=5		clay+sand n=4		overall n=15	
s1	95±6.0	5±6.0	99±0.8	1±0.8	96±3.5	4±3.5	96±4.3	4±4.3
	10±13.0	90±13.0	2±3.1	98±3.1	7±7.2	93±7.2	7±9.3	93±9.3
s2	95±5.5	5±5.5	87±19.3	13±19.3	90±9.8	10±9.8	91±12.2	9±12.2
	4±4.2	96±4.2	1±1.0	99±1.0	3±2.9	97±2.9	2±3.1	98±3.1

Table 2.5 shows that the DA gave between 85% and 95% TN classified volunteer potato pixel spectra and between 3% and 9% FN classified sugar beet pixel spectra. NN1 gave between 72% and 97% TN classified VP pixel spectra and between 1% and 21% FN classified SB pixel spectra. NN2 gave between 87% and 99% TN classified VP pixel spectra and between 1% and 10% FN classified SB pixel spectra. NN2 had better classification results than NN1 and DA.

The standard deviations were lower for NN2 with a maximum of 13.0% compared to the standard deviations for DA and NN1 with a maximum of 13.8% and 27.3%. In this situation, with the 10 fixed wavebands, sensor 1 gave better classification results on the sand soil plots, whereas sensor 2 gave better results on the clay soil plots. The overall results show that NN2 gave better classification results with both sensors than NN1 and DA.

Table 2.6 Confusion tables of the classification results using “3 fixed” wavebands. Ten optimal wavebands were adapted to the variability in each dataset. The average classification percentages and standard deviation are given for each group of n datasets and for sensor 1 (s1) and sensor 2 (s2). The upper third shows the results of the discriminant analysis (DA), the middle part shows the results of the neural network with one hidden neuron (NN1), and the lower third shows the results of the neural network with two hidden neurons (NN2).

DA	clay n=6		sand n=5		clay+sand n=4		overall n=15	
s1	76±29.0	24±29.0	76±42.5	24±42.5	70±43.4	30±43.4	74±35.0	26±35.0
	36±29.8	64±29.8	18±21.6	82±21.6	28±22.1	72±22.1	28±24.8	72±24.8
s2	85±15.4	15±15.4	66±41.1	34±41.1	84±14.2	16±14.2	78±26.4	22±26.4
	9±7.2	91±7.2	2±2.6	98±2.6	6±5.6	94±5.6	6±6.0	94±6.0

NN1	clay n=6		sand n=5		clay+sand n=4		overall n=15	
s1	67±46.8	33±46.8	74±41.6	26±41.6	71±42.7	29±42.7	70±40.9	30±40.9
	45±45.4	55±45.4	21±21.7	79±21.7	33±22.6	67±22.6	34±33.1	66±33.1
s2	86±13.8	14±13.8	68±42.8	32±42.8	80±20.1	20±20.1	79±27.3	21±27.3
	8±7.6	92±7.6	5±6.6	95±6.6	4±5.0	96±5.0	6±6.5	94±6.5

NN2	clay n=6		sand n=5		clay+sand n=4		overall n=15	
s1	81±19.5	19±19.5	75±40.3	25±40.3	71±42.7	29±42.7	77±31.8	23±31.8
	28±15.3	72±15.3	12±11.4	88±11.4	24±16.4	76±16.4	21±15.2	79±15.2
s2	88±12.2	12±12.2	69±41.0	31±41.0	83±16.8	17±16.8	80±25.9	20±25.9
	7±6.8	93±6.8	3±3.4	97±3.4	4±4.5	96±4.5	5±5.3	95±5.3

Table 2.6 shows that the DA gave between 66% and 85% TN classified volunteer potato pixel spectra and between 2% and 36% FN classified sugar beet pixel spectra. NN1 gave between 67% and 86% TN classified VP pixel spectra and between 4% and 45% FN classified SB pixel spectra. NN2 gave between 69% and 88% TN classified VP pixel spectra and between 3% and 28% FN classified SB pixel spectra. NN2 had better classification results than NN1 and DA.

The standard deviations were lower for NN2 with a maximum of 42.7% compared to the standard deviations for DA and NN1 with a maximum of 43.4% and 46.8%. For the “10 optimal” and the “10 fixed” wavebands, sensor 1 gave better classification results than sensor 2. For the “3 fixed” wavebands, sensor 2 gave better classification results, except for the analysis on sand soil, in that case sensor 1 gave better classification results.

2.5 Discussion

Measurement setup and data collection

Due to the particular construction of the ImspectorMobile, the spectra from the two sensors could not be linked to each other as similar spots on the plants were not recorded at the same time, as can be seen from the figure of the ImspectorMobile (Figure 2.1). This hampered combined selection of discriminative combinations of wavelengths of both sensors. Combinations of wavelength bands of both sensors might have had more discriminative power, but this could not be investigated with our measurement setup. Another issue with the recording setup was that not in all datasets the same amount of spectra of volunteer potato plants and sugar beets was available. The main reason for this was the growth stage of the plants. Smaller plants resulted in less recorded spectra. Of course we could have reduced the datasets to contain an equal amount of spectra for sugar beet plants and volunteer potato plants, but then a selection of spectra had to be made. In this analysis, all spectra were used to describe the variance that was in the recorded spectra.

In this study, several fields were measured, on different dates and in two years. The ImspectorMobile proved to be a robust and reliable platform for repeated measurements in the field. Especially, the pre-processing of the data with the spectral reflectance standard in the field of view was important to achieve consistent spectral reflectance recordings, as had been identified by e.g. Younan *et al.* (2004).

Wavelength selection methods DA / NN and wavelength band ranking procedure

In all analyses, with combinations of 10 wavelengths the reflectance spectra of the two crops could be discriminated. These combinations of bands were different between the plot soil types and measurement dates, resulting in a large list of discriminative wavebands. Therefore, a general set of 10 and 3 wavelengths was selected for further analysis. The 3 wavelengths that were chosen both by DA and NN were for sensor 1: 450, 765, and 855 nm and for sensor 2: 900, 1440, and 1530 nm. The 450 nm waveband is in the ultraviolet and blue reflection region in the spectrum. The 450 nm waveband is related to the chlorophyll a and b content of the leaves according to Curran (1989). The 765 nm waveband is just over the top of the red edge that is related to the chlorophyll content of the plants. The “red edge”, 700-730 nm, wavelengths are in many cases selected as discriminative wavelengths for species and crop/weed discrimination (Smith & Blackshaw, 2003). The wavelengths near and on the red edge have been reported by Cochrane (2000) to be useful for discriminating between species.
Then, the 855 nm waveband is close to 845 nm that is the center of the so-called NIR-shoulder in the reflectance spectrum which was used for discrimination according to Thenkabail *et al.* (2000). For sensor 2, 900 nm was on the maximum peak or maximum reflectance region in the NIR region (Thenkabail *et al.*, 2000). Waveband 1440 nm is related to the sugar and starch content of the foliage (Curran, 1989). Finally, from the bands that were selected, 1530 nm was one with a relatively high discriminative power within the sets of 10

bands. The 1530 nm band relates to the starch content of the plants as described by Curran (1989). This band ranked high, although it was in all cases supported by other wavelengths to be truly discriminative.

Both the statistical stepwise discriminant analysis as well as the neural network approach were able to select discriminative wavebands from the 15 datasets. The statistical stepwise forward selection was implemented straightforward through the STEPDISC procedure from SAS. The processing time of the datasets was short, within 5 seconds for one dataset. On the other hand the selection procedure with the NN took a larger amount of time. This was firstly caused by the intensive iterative training procedures that had to be restarted with randomly initialized weights in the wavelength selection stage. Secondly, the leave-one-out test had to be performed to order the list of the first ten selected wavelengths. On average the two stages of the NN procedure took 24 hours for a dataset to be finished. The NN feature selection approach from this research is often called a “wrapper method” or a “cascade method” to select discriminative features (Kohavi & John, 1997). Backstrom (2006) reported that in their cascade neural network feature selection procedures training in wrapper configuration sometimes took up to several days with neural network configurations with a similar number of input, hidden, and output neurons as used in this research. Considering the amount of time it takes to select a number of discriminative wavebands, and the limited extent to which they can be generalized to other datasets, one might doubt the practical application of this selection procedure. However, the higher classification performance of the neural network with two hidden neurons suggests that nonlinear relations between the wavebands can better discriminate between sugar beet and volunteer potato plant pixel spectra. In addition, when a selected set of ten wavebands was used for classification of a dataset; the training of the neural network was much faster, within an hour, and the classification of a dataset with a trained network was finished within seconds.

The procedure to calculate the discriminative power used in this research provided a method to summarize selected wavebands over several analyses. With that method, it was possible to generalize the selected wavebands over the datasets, without putting the original data in one larger dataset.

Classification performance with 10 optimal, 10 fixed, and 3 fixed wavebands

An increase in standard deviation on the confusion tables together with a decreased classification performance on the TN and FN percentages is seen when we go from “10 optimal” to “10 fixed” to “3 fixed” wavebands classification. This shows that it is hard to generalize discriminative wavebands to different fields, and to keep consistent high classification performance with high TN and low FN classification percentages. This effect is even larger when Table 2.4, “10 optimal”, is compared with Table 2.6, “3 fixed”, when the number of variables used for discrimination is decreased to three fixed wavebands. In that comparison, for the sand plot datasets with NN2, the TN and FN percentages were 100±0.1% and 1±1.3% for the “10 optimal” wavebands and were 75±40.3% and 12±11.4% for the “3 fixed” wavebands respectively. Other research studies found similar results and also concluded that it is hard to find generalized sets of wavebands for discrimination and classification. For example, Smith and Blackshaw (2003) concluded that it is unlikely that a single spectral signature can be used for discrimination between weeds. Rather a combination of spectra and canopy structure or growth stage may play a role. In addition, Girma *et al.* (2005) concluded that spectral measurements differed with the growth stage of the plants. The change in reflectance pattern required accurate analysis to classify crops and weeds. Different vegetation indices and bands were needed to obtain high classification performance in different growth stages.

Goel *et al.* (2003) used similar selection and classification procedures as used in this research and classified hyper-spectral data of weeds in corn with decision trees and neural networks. They found that different growth stages had different reflection characteristics and that resulted in up to 22% misclassification using decision trees. Slightly better results were obtained with neural networks, however the classification rules derived using neural networks were hard to understand. Our research relates to the selection methods that were performed with statistical linear discriminant analyses by Vrindts *et al.* (2002). However, in their research the crops and weeds were measured on specific growth stages and changing light conditions, which did not result in specific wavelengths for crop-weed detection. In this research, the light conditions were constant and measurements were done on different dates on the same plants. This resulted in specific sets of wavebands that could be used for discrimination between VP and SB pixel spectra. According to Vrindts *et al.* (2002) wavelengths in the visible and near infrared regions exhibit great power in discriminating species from each other, which agrees to the results from our analysis as both for sensor 1 and 2 discriminating wavebands were selected. Borregaard *et al.* (2000) showed in a lab experiment with sugar beets, potato plants, and weeds that classification performances between 70 and 90% could be reached with similar statistical DA methods. However, no discrimination was made between sugar beet and potato plants spectra. Furthermore, Piron *et al.* (2008) did a study to select the most efficient wavelength bands for discriminating weeds from a carrot crop. With three wavelength bands their classification accuracy was highest at 72%, which is in the same order as the results achieved in this research with the “3 fixed” dataset classification. They used a quadratic discriminant analysis, similar to our discriminant analysis. Compared to these results our results compare favorably, especially for the neural network classification.

2.6 Conclusion

With the ImspectorMobile, vegetation reflection spectra were successfully repeatedly gathered in two fields, on seven days in two years that resulted in 15 datasets. Both in the visual and in the near-infrared reflection region, combinations of wavelengths were responsible for discrimination between sugar beet and volunteer potato plants. Two feature selection methods, discriminant analysis (DA) and neural network (NN), succeeded in selecting sets of discriminative wavebands, both for the range of 450-900 nm and 900-1650 nm. First, 10 optimal wavebands were selected for each of the 15 datasets. Second, by calculating the discriminative power of each selected waveband, 10 fixed wavebands were selected for all the 15 datasets. Third, 3 fixed wavebands were determined. These had been identically selected both by DA and NN and were for sensor 1: 450, 765, and 855 nm and for sensor 2: 900, 1440, and 1530 nm. With the three sets of wavebands, classifications were performed with a DA, a neural network with 1 hidden neuron, NN1, and a neural network with two hidden neurons, NN2.

The maximum classification performance was obtained with the “10 optimal” waveband sets, where the percentages were 100±0.1% and 1±1.3% for TN and FN respectively for the average of 5 sand plots. This was for the NN2 method and sensor 2. In general the NN2 method gave the best classification results, followed by DA and finally the NN1 method.

When the 15 “10 optimal” waveband sets were generalized to a set of “10 fixed” wavebands, the classification results were still at reasonable level of a minimum performance at 87% TN and 1% FN for the NN2 classification method. However when a further reduction and generalization was made to “3 fixed” wavebands, the classification results were poor with a minimum performance of 69% TN and 3% FN for the NN2 classification method. So, for the best classification results it is required that the sensor and classification system adapt to the specific field situation, to optimally discriminate between VP and SB pixel spectra.

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Chapter 3

Colour based detection of volunteer potatoes as weeds in sugar beet fields using machine vision

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3.1 Abstract

The possible spread of late blight from volunteer potato plants requires the removal of these plants from arable fields. Because of high labour, energy, and chemical demands, a method of automatic detection and removal is needed. The development and comparison of two colour-based machine vision algorithms for in-field volunteer potato plant detection in two sugar beet fields are discussed. Evaluation of the results showed that both methods gave closely matched results within fields, although large differences exist between the fields. At plant level, in one field up to 97% of the volunteer potato plants were correctly classified. In another field, only 49% of the volunteer plants were correctly identified. The differences between the fields were higher than the differences between the methods used for plant classification.

Keywords: image analysis, crop/weed classification, plant-specific weed control

3.2 Introduction

Potatoes are one of the most important crops in the Netherlands. They are grown on a total area of 180000 ha. Unfortunately, they are vulnerable to disease, especially to the outbreak of late blight caused by *Phytophthora infestans*. Late blight is one of the most important potato diseases that is spread, for instance, by volunteer potatoes. Volunteer potatoes are potato plants that have survived the winter due to lack of frost. They can be responsible for infesting up to 80000 plants/ha during the following year after crop rotation has taken place. In this way, volunteer potatoes spread pests and disease to regular potato crops in neighbouring fields (Turkensteen *et al.*, 2000; Boydston, 2001). In the Netherlands, farmers are under a statutory obligation to remove volunteer potatoes from the field by the 1st of July. There is a definite need for methods to selectively detect and remove volunteer potatoes. At present, no selective chemicals are available to eliminate the potato tubers or volunteer potatoes in sugar beet fields (Boydston, 2001). The existing method of manually removing volunteer potatoes with up to 30 h/ha of manual labour is too time consuming and therefore too costly (Paauw & Molendijk, 2000). Besides manual removal of volunteer potatoes, band spraying machinery is used to apply glyphosate between rows of sugar beets. However, the effectiveness of band sprayers is limited, as only between 20 and 80% of volunteer potatoes are removed, while up to 25% of sugar beets may be unintentionally killed (Reijnierse, 2004).

In 2004, a project was initiated with the goal to develop an economically attractive automatic volunteer potato detection and control system. This paper discusses one part of such a system, a colour-only based technique to detect volunteer potato plants in sugar beet fields using machine vision. The objective was to develop a method based on a one time short learning process for a field under certain circumstances and subsequently classify the image pixels and plants from that field. Colour vision as a detection means was chosen because of the reasonable price of the hardware and its proven applicability (Lee *et al.*, 1999) in other agricultural applications. By using colour vision, several features can be chosen to create a plant specific sensor. Shape, colour and texture are commonly used features for detection of plants in images (Woebbecke *et al.*, 1995). Compared to shape and texture-based detection, colour based detection algorithms are faster and less complex (Perez *et al.*, 2000). However, the colour based detection system needs to overcome the challenge of operating under natural lighting conditions during various crop growth stages between April and July.

Earlier research (Nieuwenhuizen *et al.*, 2005) has shown that with a 3-CCD camera, volunteer potato plants could be distinguished based on colour only. One method used a combination of K-means clustering, a Bayes classifier, and a resulting colour lookup table. Another method investigated was a neural network based classification routine. Using the method with the lookup table 96% of the volunteer potato plants could be detected in a sugar beet crop. In that approach, the plant objects in the images were classified by human inspection of the pixel classification result.

The research reported in this paper was built on the results of the earlier research by testing the performance of those two colour-only based detection algorithms in two fields. Also, a low-cost Bayer filter CCD camera was used and, finally, the human operator based visual object classification method was automated.

3.3 Materials and methods

Image acquisition

Image acquisition was achieved using a Basler A301f colour camera with a 4.2 mm lens mounted perpendicular to the soil surface on a in-house made three-wheel platform as shown in Figure 3.1. Image acquisition was triggered by a distance sensor on one of the wheels, such that images were taken every 0.5 m in the driving direction. The camera was mounted such that an image covered one beet row and two thirds of the soil area between two adjacent rows. Images (640×480 pixels) were stored on a Pentium III PC. During image acquisition, the colour gains and the shutter time of the camera were adjusted continuously based on a grey reference plate which was placed at the bottom side of the field of view of the camera. This adaptive grey balance was applied to maintain a constant quality of the acquired images under variable outdoor light conditions.

Figure 3.1 Measurement setup during the field experiment. A: Grey reference plate; B: camera; C: desktop PC; D: wheel trigger.

Experiments

In spring 2005, the platform was pushed forward by hand at approximately 1 m/s and images were acquired on two fields with a sandy soil. On May 26, 100 images were acquired under sunny conditions on field 1, where the sugar beet plants were in the two- to four-leaf stage. On June 2, another 220 images were acquired under cloudy conditions in field 2, where the sugar beet plants were in the four-leaf stage. Figure 3.2 shows two illustrative examples of images taken on field 1 and 2 respectively. The images clearly demonstrate the effects of different lighting conditions. It was also observed that about 25% of the images did not contain any volunteer potato plants.

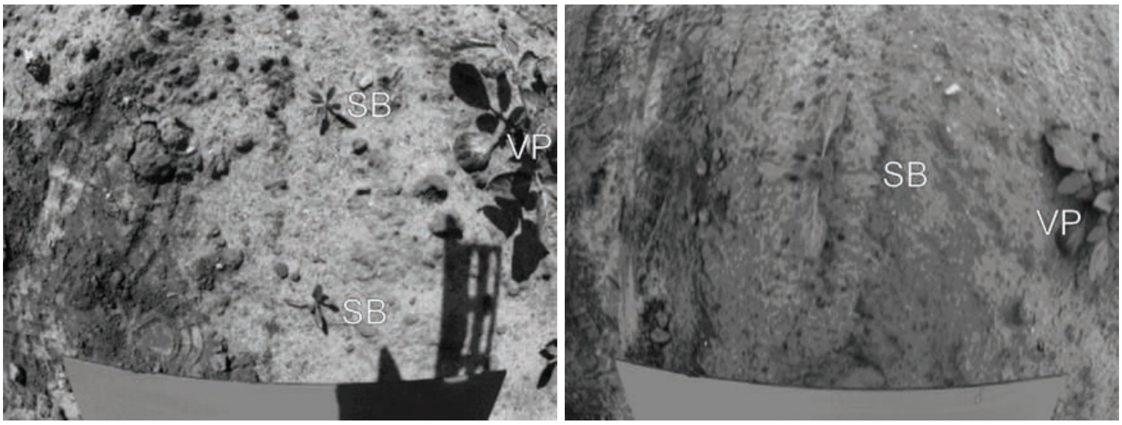

Figure 3.2 Sugar beet plants (SB) and volunteer potato plants (VP) in field 1 (left) acquired under sunny conditions and field 2 (right) acquired under cloudy conditions. The grey reference plate is shown at the bottom of the images. The growth stage of the sugar beets in field 2 was larger than in field 1.

Image processing and volunteer potato classification

Image processing consisted of three main steps, *i.e.* an image pre-processing, pixel classification and plant object classification.

Image pre-processing

The first step of image-processing was to correct the images for lens distortion using a nonlinear calibration routine. This resulted in a correct representation of the area of the plants in the images used for learning and classification. Secondly, the green plant material was segmented from the soil background. This second step was done to reduce the calculation time in classifying plant parts into volunteer potato plant and non-volunteer potato plant regions. For this segmentation task, the excessive green parameter (Woebbecke *et al.*, 1995) (Equation 3.1) and a threshold were used. The threshold for the excessive green value was set at 20, which was based on the interclass variance in the histograms of the images. One static threshold could be used as intensity and colour of the images were kept constant using the reference plate as shown in Figure 3.1.

$$ExcessiveGreen = 2 * G - R - B \tag{3.1}$$

where
G = Green pixel value
R = Red pixel value
B = Blue pixel value

After background elimination, the remaining plant pixels were transformed using the EGRBI transformation matrix (Steward & Tian, 1998) as defined in Equation 3.2. This transformation separates the intensity information from colour information and allows further analyses based on colour only.

$$\begin{bmatrix} EG \\ RB \\ I \end{bmatrix} = \begin{bmatrix} \frac{-1}{\sqrt{6}} & \frac{2}{\sqrt{6}} & \frac{-1}{\sqrt{6}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{-1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{3.2}$$

where
EG = Excessive Green
RB = Red minus Blue
I = Intensity

The distribution of the EG and RB values from the plant pixels of sample images from field 1 and field 2 are shown in Figure 3.3. It shows two colour groups and the possibility of using EG and RB values to segment potato pixels from sugar beet pixels. The visually separable distribution of sugar beet and volunteer potato colour groups in the EG-RB plane was the reason for choosing EG and RB as suitable features for volunteer potato detection.

Pixel classification
For each field, classification was based on five learning images. Both classification methods used the same learning images. The learning images were randomly chosen. Therefore, the results could indicate whether static or adaptive methods would better classify volunteer potato plants. In the results section two fields, five learning images, and two methods yielded 20 classification runs.

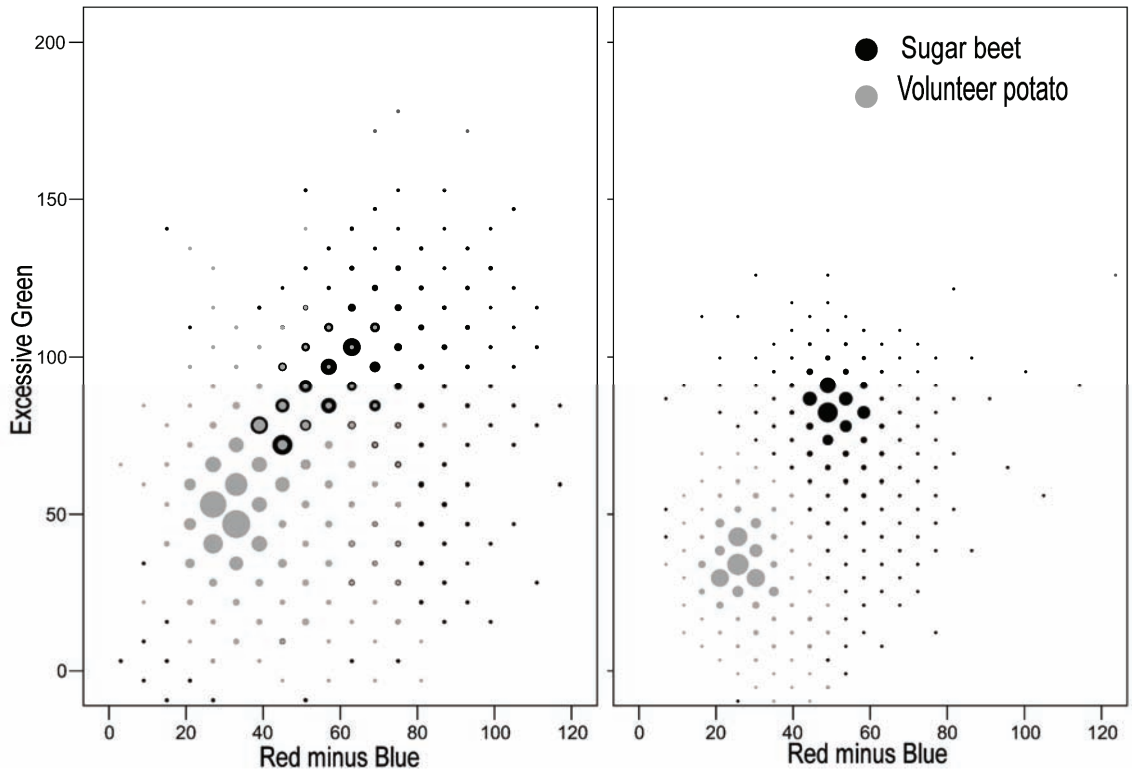

Figure 3.3 EG and RB pixel values for potato and sugar beet plants from field 1 (left) and field 2 (right), larger circles represent more pixels with identical values.

For pixel classification two methods were used. The first method was a combination of K-means clustering and a Bayes classifier (Tang, 2002). For clustering of image pixels, the EG and RB features were used together with the Euclidean distance measure. The plant pixels were clustered using the K-means algorithm with eight randomly chosen cluster centres as starting point. Volunteer potato plant clusters were identified in the EGRB clustered image and labelled manually in the learning image. The corresponding RGB values of the labelled clusters were input as *á priori* data, representing the volunteer potato class for that specific field, to a Bayes classification routine as described by Gonzalez and Woods (1992). After that, all possible (256^3=16777216) RGB colour values were input to the Bayes decision function and a Lookup Table (LUT) was generated, consisting of all RGB values and a boolean value for membership of volunteer potato pixels. Finally, all pixels in the images from field 1 and field 2 were classified using the subsequent five different lookup tables from the five learning images for field one and the subsequent five LUTs from the five learning images for field two.

The second method was to train an Adaptive Resonance Theory 2 (ART2) Neural Network for Euclidean distance-based clustering (Pao, 1989) and then use its weights to form a classifier. An ART2 Neural Network is an unsupervised learning method that is able to adaptively cluster continuous input patterns according to the distribution of the dataset. The iterative learning process decides to which cluster an input pattern of EGRB pixel colour values belongs. In contrast with the fixed number of clusters using K-means clustering, an

ART2 neural network produces a variable number of clusters in accordance with the distribution of the data in the learning image. ART2 can handle continuously valued input patterns and a vigilance parameter is set to guard the cluster splitting process. The weights of the neural network contain the cluster representation in EGRB colour space and were saved together with the manually identified volunteer potato clusters in the learning images. Finally, these ten weight files were used for classification of all the pixels from the images from field 1 and field 2.

So, after the 20 pixel classification runs using both methods, the classification results were evaluated. For this purpose, reference data are necessary to evaluate the performance of the classification procedures. After passing the excessive green threshold as described earlier, all 320 images of field 1 and 2 were visually evaluated and judged. With objects labelled as volunteer potato and sugar beet, Figure 3.4 shows a representative example of these 320 evaluated images. These images were used as a reference to evaluate the performance of the classification and to define true positive and false positive classified pixels. True positive percentage was defined in Equation 3.3 and false positive percentage was defined in Equation 3.4.

$$\text{True positive pixels \%} = \frac{\text{Potato pixels classified as potato pixels}}{\text{Total reference potato pixels}} \cdot 100\% \qquad (3.3)$$

$$\text{False positive pixels \%} = \frac{\text{Sugar beet pixels classified as potato pixels}}{\text{Total reference sugar beet pixels}} \cdot 100\% \qquad (3.4)$$

The number of classified potato and sugar beet pixels in Equations 3.3 and 3.4 was derived from the classification results and the total number of potato and sugar beet pixels was calculated from the binary reference images.

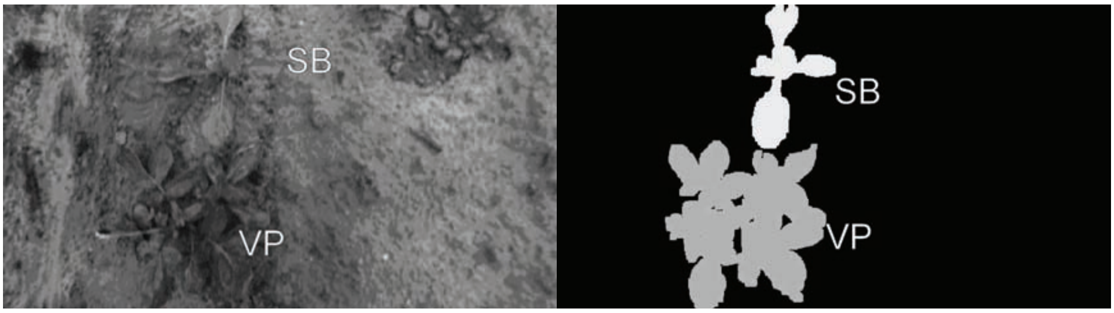

Figure 3.4 Sugar beet plants (SB) and volunteer potato plants (VP) in an image after correction for lens distortion (left) and binary reference image (right)

Plant object classification

More importantly, the results were evaluated at plant object level as we are not interested in detected pixels, but rather volunteer potato plants. A plant object was either classified as potato plant or as sugar beet plant. This decision was based on the percentage pixels classified in the object and a threshold, as defined in Equation 3.5.

$$\begin{array}{lll} \%\,\text{Classified pixels in object} \geq \text{threshold} & \Rightarrow & \text{object} \in \text{potato plants} \\ \%\,\text{Classified pixels in object} < \text{threshold} & \Rightarrow & \text{object} \in \text{sugar beet plants} \end{array} \tag{3.5}$$

As in every classification problem, a trade-off between correct classification and misclassification was present in the threshold level in Equation 3.5. We decided to accept a misclassification rate of the sugar beet plants of 5%, based on the fact that current –non plant specific- band spraying machinery may even remove up to 25% of the sugar beet plants. The threshold level was defined at a level where the misclassification of sugar beet plants was as close as possible to 5%, but 5% misclassification could not always be attained due to the integer number of sugar beet plants available in the images.

For each of the twenty runs the percentage true positive classification and false positive classification of plants was calculated according to Equations 3.6 and 3.7. The total number of potato and sugar beet plants was calculated from the binary reference images.

$$\text{True positive objects}\,\% = \frac{\text{Potato plants classified as potato plants}}{\text{Total potato plants}} \cdot 100\% \tag{3.6}$$

$$\text{False positive objects}\,\% = \frac{\text{Sugar beet plants classified as potato plants}}{\text{Total sugar beet plants}} \cdot 100\% \tag{3.7}$$

3.4 Results

Pixel classification

The results of pixel classification of the two fields are given in Table 3.1 and an example of pixel classification is shown in Figure 3.5. Firstly, the true positive classification in field 1 shows that between 3 and 41% of the potato plant pixels were classified true positive. Within field 1, the neural network (NN) approach had a higher percentage volunteer potato pixels classified compared to the K-means/Bayes approach (LUT). Similarly, in field 2, between 11 and 52% of the pixels were correctly classified and again, the NN showed higher percentages volunteer potato pixels classified.

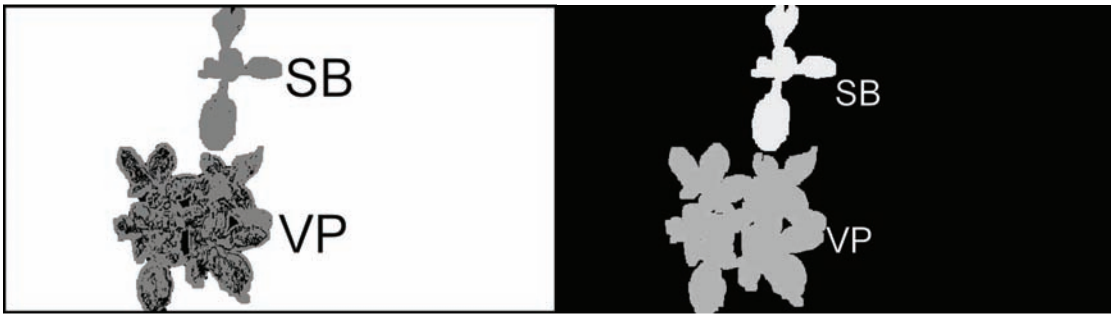

Figure 3.5 Sugar beet plants (SB) and volunteer potato plants (VP) in an image with classified pixels in black (left image) and its corresponding image with classified plant objects based on the threshold from Equation 3.5 (right image).

Secondly, the false positive classification shows that in field 1 between 5 and 22% of the pixels were misclassified. In contrast, in field 2 the misclassification of sugar beet pixels was much smaller between 1 and 7% if we do not take into account learning image 6. Learning image 6 showed almost no visual colour differences between volunteer potato and sugar beet plants. Therefore, it was hard to choose clusters representing the green colours of the volunteer potato plant but not the green colours of the sugar beet plants. As a result, the false positive classification rate was higher than the true positive classification rate. Finally, the pixel classification results show that choosing a different learning image influenced the true and false positive percentages.

Table 3.1 Pixel classification results for field 1, 100 images, field 2, 220 images when using two classification methods and five learning images. The percentage of classified pixels given are the average over the classification runs. LUT = Bayes classification implemented by lookup tables, NN = ART2 Neural Network classification implemented by saved weights of the neural net.

	Field 1			Field 2		
Classification method	Learning image	Sugar beet False Positive	Volunteer potato True Positive	Learning image	Sugar beet False Positive	Volunteer potato True Positive
LUT	1	6.22	9.73	6	21.85	14.85
LUT	2	6.86	13.61	7	0.43	18.42
LUT	3	18.97	21.22	8	0.12	11.04
LUT	4	8.07	8.20	9	0.05	12.79
LUT	5	9.47	9.48	10	2.31	27.30
NN	1	8.26	16.34	6	6.99	23.83
NN	2	7.51	18.24	7	3.90	51.80
NN	3	22.14	41.38	8	0.12	11.04
NN	4	9.33	8.77	9	0.37	22.16
NN	5	4.73	2.51	10	0.78	27.70

Plant object classification

Pixel classification results showed in general a higher true positive rate for volunteer potato pixel classification than for sugar beet. Therefore, one can distinguish between volunteer potato and sugar beet based on the classification percentage. So, this information was used to set up the plant object classification routine. Table 3.2 shows the true and false positive plant classification percentages as well as the threshold used to classify objects as volunteer potato of sugar beet using equation 3.5. Due to the integer characteristics of the number of crop plants, a misclassification rate of 5% on the sugar beets could not always be achieved. Nevertheless, the closest approximation is given in Table 3.2. The true positive rate in field 2 for learning image 6 is much higher than the true positive rate in field 1. The zero percent classification rate of image 6 in field 2 was caused by the poor pixel classification result where the false positive percentage classified was larger than the true positive percentage classified. This negatively affected the plant classification results and the threshold level of 38% still resulted in 0.0% classified volunteer potato plants.

Table 3.2 Plant classification results for both fields. Threshold % indicates the percentage of pixels in a plant object over which it was positively classified as defined in Equation 3.5.

	Field 1				Field 2			
Classification method	Learning image	False Positive SB %	True Positive VP %	threshold %	Learning image	False Positive SB %	True Positive VP %	threshold %
LUT	1	4.55	48.94	10	6	4.80	0.00	38
LUT	2	5.30	34.04	17	7	4.80	95.65	2
LUT	3	5.30	17.02	27	8	2.88	81.52	1
LUT	4	5.30	14.89	13	9	0.96	85.87	1
LUT	5	6.06	17.02	14	10	4.80	81.52	12
NN	1	6.82	48.94	15	6	5.28	55.43	19
NN	2	5.30	34.04	21	7	5.04	94.57	14
NN	3	5.30	29.79	47	8	2.88	81.52	1
NN	4	3.79	12.77	12	9	3.36	88.04	1
NN	5	5.30	10.64	6	10	6.00	96.74	1

3.5 Discussion

Pixel classification

The main reason for the differences in classification results between field 1 and field 2 was the overlapping distributions in EG-RB space of field 1 images (Figure 3.3). In field 1 the two classes were not well separated. Therefore, the false and true positive classification results were closer to each other in field 1. The differences within the fields were caused by the quality and contents of the learning image. Although the learning images were chosen randomly, they may not have represented the actual colour distribution of the two classes for the complete field, from which learning image 6 was an example case. When looking into the difference of two classification methods, larger differences in performance between the Bayes classifier and the neural network were expected because the latter could adapt itself better to the variation of image conditions during the clustering process. However, similar to Marchant and Onyango (2003) found out there were not large differences in pixel classification performance between a Bayesian classifier and a neural network classification routine. A reason for the similarities in classification performance was that both algorithms use the Euclidean distance between the pattern and the cluster centres as a decision measure for cluster membership.

Plant object classification

Field 2 showed higher numbers of volunteer plants were true positive classified. These higher true positive rates were reached with lower threshold levels in plant pixels classified. This indicates that a relatively larger amount of volunteer potato pixels was already classified when 5% of misclassification in sugar beets was reached. On the other hand, field 1 gives lower true positive rates, this might be due to smaller colour differences between sugar beet and volunteer potato plants as shown in Figure 3.3, which was due to the direct sunlight illumination that often results in specular effects and colour vanishing on plant pixels. The neural network gave a slightly better approach when using learning image 3, 6, 9 and 10. This indicates that the adaptive clustering was successful in these learning images. Possibly using multiple learning images would increase the classification results, but this was not within the objectives of this research. Learning image 6 from field 2 showed no volunteer potato plants classified when the LUT was used. This was due to the high amount of misclassification in the sugar beet plants. When the threshold level of 5% of sugar beet plants was used, still no volunteer plants had more pixels classified than the threshold level of 38%. This resulted in true positive classification rates between 11 and 49% in field 1 and in true positive classification between 56 and 97% in field 2 when learning image 6 was omitted. With the automatic classification procedure as described in this report, it was possible to reach over 95% true positive classification, similar as previously predicted (Nieuwenhuizen *et al.*, 2005).

General

The results show a discrepancy in classification performance between the two different sampling days. Several factors are responsible for the discrepancy. Firstly, the outdoor lighting conditions between the days were different. In field 1 the images were acquired under sunny conditions. This caused shadows in the images and shadowed leaves have different colours than leaves in the sun or in overcast conditions. These shadow effects within plants will not be corrected for by changing and updating the white balance. Also, direct sunlight causes colour fading in images. The images taken under overcast conditions did not have shadow effects, which largely explains the better classification results. Secondly, the growth stage of the plants changed between the days of image acquisition. Figure 3.2 shows that the sugar beet plants are larger in field 2. Therefore the number of pixels available as training data is larger. This resulted in a better representation of the two classes used.

The algorithms as applied in this research were colour based only and were not adaptive to colour changes of the plants in the field. The classification algorithms were trained on five learning images resulting in static classifiers. The changing thresholds in Table 3.2, needed tot maintain constant misclassification rates of approximately 5%, indicate that adaptive methods are needed to classify volunteer potatoes and sugar beets in a field situation correctly. Therefore, possible improvements on our current classification scheme can be made in several ways. Firstly, the detection algorithms could be made adaptive to colour changes, for example by iteratively learning the lookup table or the neural net. Also taking the average colour of plants might be more efficient for learning and classification of plant objects, as it is less computational intensive. Secondly, more plant features like texture, shape, and near infra red reflection properties could be used. Hemming and Rath (2001) also included crop row distances and morphological features of the plant objects to improve the classification results. Especially an adaptive method that takes care of changing plant parameters in the field should be able to outperform static classification methods based on single static learning images.

The software showed that applying a lookup table was four times faster than the neural network implementation, although the applications were not optimised for processing speed. The reason for this difference was that applying a lookup table was computationally less expensive than the computation of a neural network-based classifier.

Some mixed binary objects, due to occluded leaves, were present in our data. In field 1, two volunteer plants occluded sugar beet plants, this was 1.1% of the total plants appeared in the images. In field 2, eleven plants occluded, this was 2.2% of the total number of plants. This amount was higher in field 2 due to the larger growth stage of the crop and volunteer plants. This number of occlusions in our data could not be of major influence on the results. Anyway, for calculation of the results, the occluded objects were not taken into account, as they were labelled in a separate group when the reference images were made.

3.6 Conclusions

In this research, two colour-based classification schemes, namely an Adaptive Neural Network and K-Means clustering/Bayes classification scheme, were developed and field tested for volunteer potato plant detection in sugar beet fields. Up to 97% of the volunteer potato plants could be detected in a test field under cloudy conditions by using the neural network classification. In another test field under sunny conditions, up to 49% of the potato plants could be detected by both the neural network and the Bayes classification scheme. The colour-based algorithms were not yet suitable to detect more than 97% of the volunteer potato plants in different field situations. The performance of the volunteer potato detection algorithm under outdoor field conditions depended on the both plant growth stages and light conditions. The results showed that an improved adaptive method is needed to achieve a consistent classification performance over fields. Adaptive methods for plant object classification are currently included and evaluated in a practice situation.

3.7 Acknowledgements

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Chapter 4

Adaptive detection of volunteer potato plants in sugar beet fields

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4.1 Abstract

Volunteer potato is an increasing problem in crop rotations where winter temperatures are often not cold enough to kill tubers leftover from harvest. Poor control, as a result of high labor demands, causes diseases like *Phytophthora infestans* to spread to neighboring fields. Therefore, automatic detection and removal of volunteer plants is required. In this research, an adaptive Bayesian classification method has been developed for classification of volunteer potato plants within a sugar beet crop. With use of ground truth images, the classification accuracy of the plants was determined. In the non-adaptive scheme, the classification accuracy was 84.6 % and 34.9 % for the constant and changing natural light conditions respectively. In the adaptive scheme, the classification accuracy increased to 89.8% and 67.7% for the constant and changing natural light conditions respectively. Crop row information was successfully used to train the adaptive classifier, without having to choose training data in advance.

Keywords: machine vision, adaptive Bayesian classification, weed detection

4.2 Introduction

Volunteer potato is a serious weed in many potato growing regions where winter temperatures often are not cold enough to kill tubers left in the ground after harvest (Lutman & Cussans, 1977; Boydston, 2001). Plants sprouting from overwintered tubers are difficult to control in sugar beet, where no selective herbicides are available (Cleal, 1993). As a result of poor control, volunteer potatoes affect other crops in the crop rotation. Volunteer potato harbors diseases like *Phytophthora infestans*, insects and nematode pests of potato, negating the benefits of crop rotation (Turkensteen *et al.*, 2000). Volunteer potatoes have to be removed to increase the benefit of crop rotation. Applying glyphosate to volunteer potato plants is the most effective control method but is very labour intensive (Paauw & Molendijk, 2000) and therefore has to be automated. Precise application of glyphosate is required to prevent crop damage as glyphosate is a non-specific systemic herbicide (Giles *et al.*, 2004). Therefore, precise application is needed on volunteer potato plants and application on sugar beets should be prevented. The automation of application of glyphosate to volunteer potato plants is the objective of current research. Essentially, an automated volunteer potato removal device consists of a system that detects and a system that removes or kills unwanted plants. A system analysis revealed that a vision system for such a precise control system should satisfy the following design criteria: (1) square centimeter precision within the sugar beet row seed line to assure targeted application on volunteer potato only, (2) handle daylight and weather variability, (3) handle within-field and between-field variability of crop and volunteer potato plant features like growth stages, occlusions and colours and, (4) no offline training data should be used, online training is required.

Weed detection systems have evolved from large scale remote sensing techniques to high resolution machine vision detection systems (Thorp & Tian, 2004). Nevertheless, machine vision based systems for precise weed control at square cm level have hardly been researched besides, for example, a tomato seedling weed detection and removal application by Lee *et al.* (1999) and sugar beet and weed detection by Astrand (2005). Nieuwenhuizen *et al.* (2005), showed that colour-based detection of volunteer potatoes is to some extent feasible, although problems occurred with occlusions of plants, square centimeter precision could not be attained and variations between fields and daylight variations could not be handled. Marchant and Onyango (2001) showed methods for daylight invariant classification of vegetation from the soil background but they did not investigate classification of crops and weeds with their invariant image maps. For crop and weed classification, Astrand (2005) made an Integrated Plant Classifier (IPC) that combined *a priori* geometrical planting data and *a posteriori* features of the plant information. The combination of *a priori* and *a posteriori* information improved classification of sugar beet seedlings and weeds in the field. Tillett *et al.* (2002) gave a promising example of how *a priori* geometrical cropping information like row recognition can be gathered in the field. All algorithms that have been proposed for machine vision detection of weeds and crops use features of reflectance of the vegetation to define a certain decision function. Classification functions applied with machine vision use features that are in general identified as colour, shape and texture. El Faki *et al.* (2000) and Woebbecke *et al.* (1995b) applied colour features for weed detection. Shape features were applied by for example Guyer *et al.* (1986) and Woebbecke *et al.* (1995a). Woebbecke *et al.* (1995a) described problems with regard to shape features like occlusions of leaves; these could be due to the growth stage of the crops that were measured. Texture features were used for crop and weed detection by Burks *et al.* (2000). To derive classification functions from the features, most methods described in the literature need separate labeled training datasets of the classes. However, these training data are not always available. In addition to availability of training data, training images do not always give consistent classification results (Nieuwenhuizen *et al.*, 2007). The results depend on the actual properties of the weeds and crops within the training images which is not known beforehand, and probably do not sufficiently represent the crop and weed population within the field.

The objective of this research was to extend weed detection methods to match the design criteria as mentioned before: (1) include row recognition information for automatic classifier training purposes, (2) include more features to increase correct classification rates and, (3) adaptively classify vegetation at square centimeter precision to handle variability and occlusion of plants.

4.3 Material and methods

In spring 2006, data were gathered with a color camera for row recognition (VGA resolution, 640x480 pixels) and a color camera for crop recognition (SXGA resolution, 1392x1040 pixels). The camera for row recognition was mounted at a 45 degree angle looking forward and was fitted with a 4.8 mm focal length lens and gave a field of view containing three or more crop rows, as shown in Figure 1. The row recognition camera had automatic shutter-time and white balance enabled based on the complete scene that was imaged. The crop recognition camera was mounted perpendicular to the soil surface. A 6 mm focal length lens resulted in a field of view of 1.0 m length and 0.7 m width containing one sugar beet row. The angles of the cameras and the fields of view were calibrated before the experiments were started in the field. Shutter time and white balance for the crop recognition camera were automatically adjusted based on a grey reference board with 50% reflectance (Fotowand, 2006) mounted in the field of view of the camera. The adjustment was done after each image was captured, and was done in the camera hardware.

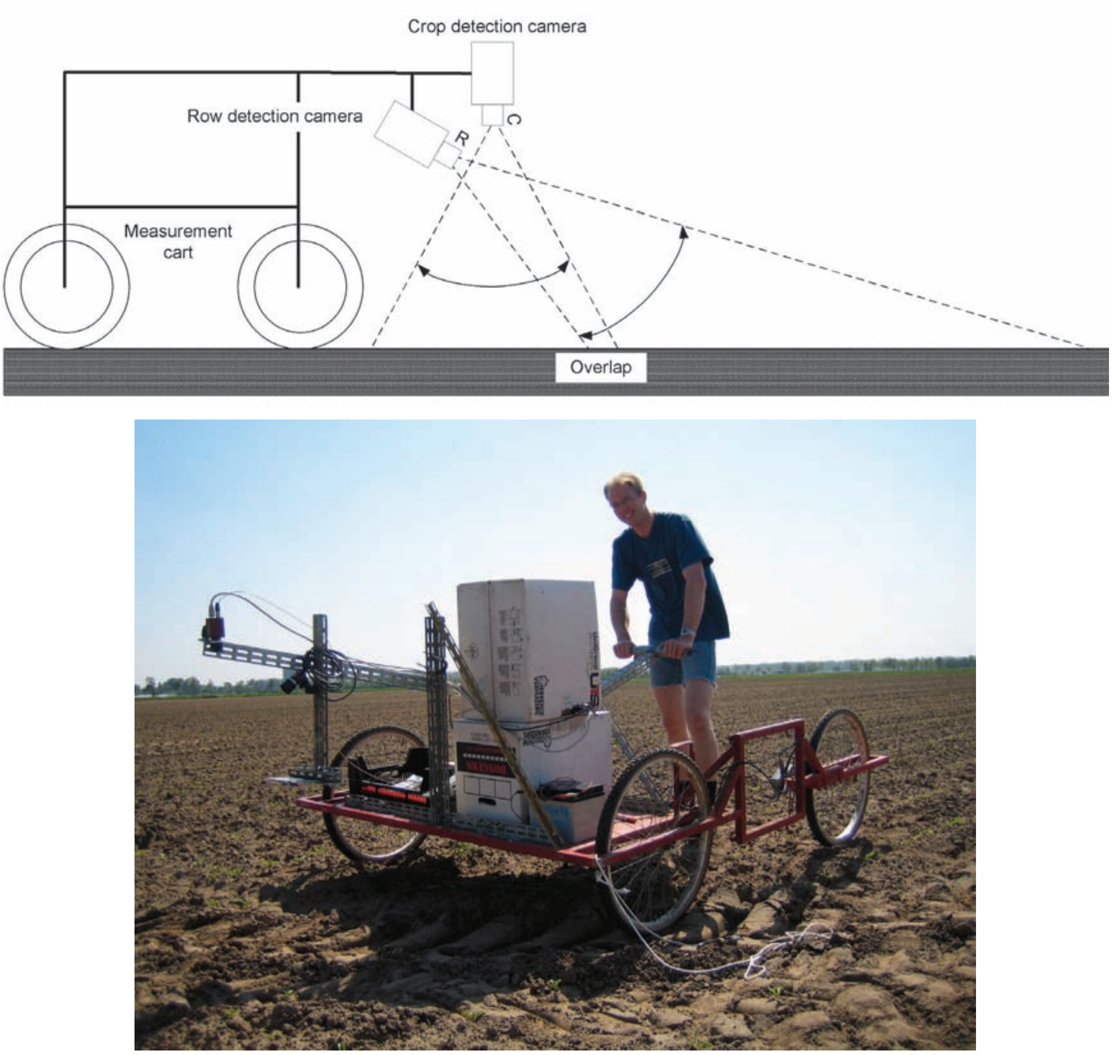

Figure 4.1. Manually operated mobile measurement setup with row recognition camera (R) and crop recognition camera (C). The field of view of the row recognition camera has an overlap of 0.1 m with that of the crop recognition camera.

An optical wheel encoder triggered both cameras every 500 mm to acquire an image, therefore plant recognition camera images had 50% overlap. The images were recorded at walking speed between 0.5 and 1.0 m s^{-1}. Images were recorded online and analyzed offline.

The classification procedure of the images was:

For image = 1 to N

{

1) *Determine crop row position in row recognition image*
2) *Create vegetation grid cells of 100 mm^2 in crop recognition image*
3) *Determine crop row width*
4) *Determine feature values for each vegetation grid cell*
5) *Update a priori training data for classification*
6) *Normalize the feature values*
7) *Classify each grid cell and show decision*

}

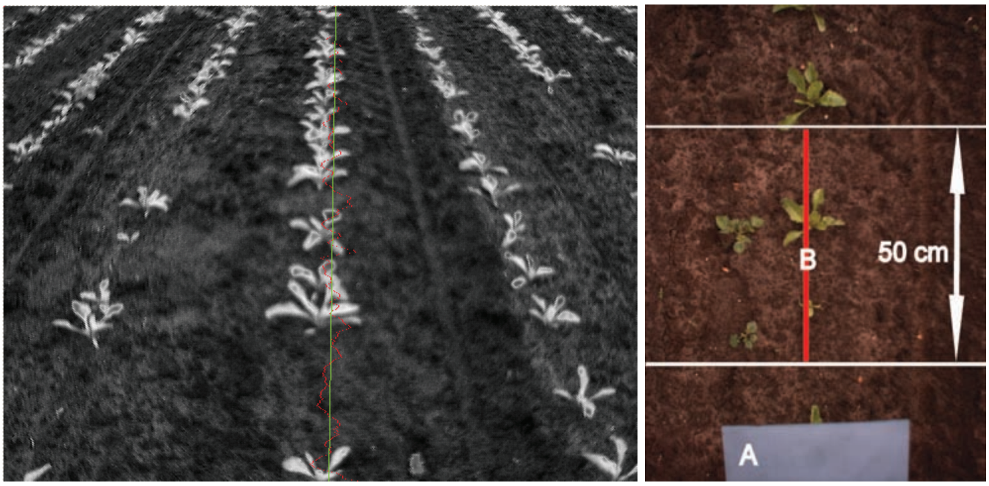

Figure 4.2. Crop row detection image, after excessive green transformation (left) and overlaid crop row position (B) in plant recognition image (right). The middle 0.5 m of each image was used for recognition. The grey reference for shutter time and white balance correction is annotated with (A).

Vegetation was highlighted from the soil background in both the row and crop recognition images using the excessive green transformation defined by Woebbecke (1995b), Excessive Green, EG = 2·G-R-B. In the crop recognition images, a threshold on the excessive green values was set at 10 based on examining histograms of the data. Images of the row recognition camera gave information on the crop row position using an algorithm based on Tillett *et al.* (2002). Our row recognition algorithm contained a template with three Gaussian bell shaped curves that were convolved with the actual crop row image. The row position from the convolution procedure was used as *a priori* information to determine which plants grow within and which ones grow between the crop row in the crop recognition image. After the convolution procedure, the calculated crop row position was overlaid on the corresponding crop recognition image and the width of the sugar beet crop row was determined using a histogram approach. The histogram is made from an image where the bins represent the number of green pixels in the driving direction in the current image, resulting in a peak at the position of the sugar beet plants. The width of the peak represents the width of the sugar beet crop. Subsequently, the crop recognition image was split into grid cells that represented about 100 mm^2 at the soil surface. If a grid cell contained vegetation, based on the excessive green value from Woebbecke (1995b), six features were determined for the specific grid cell. The features determined were: (1) distance to crop row, (2) mean red value, (3) mean green value, (4) mean EG value, (5) mean red-blue (RB) value and, (6) texture in terms of the length of edge segments. The distance to crop row is the perpendicular distance of the grid cell to the detected crop row position measured in mm. The mean red and mean green values were determined from histograms of the actual grid cell. The mean EG and mean RB values were calculated with the EGRBI transformation matrix (Equation 4.1).

$$\begin{bmatrix} EG \\ RB \\ I \end{bmatrix} = \begin{bmatrix} \frac{-1}{\sqrt{6}} & \frac{2}{\sqrt{6}} & \frac{-1}{\sqrt{6}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{-1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{4.1}$$

According to Steward & Tian (1998), this transformation is a rotation of the RGB coordinate system such that the resulting I-coordinate is collinear with the intensity axis. The EG and RB coordinates span a color plane with in one direction the greenness and in the other perpendicular direction values ranging from blue to red.

The texture measure was calculated as the length of the edge segments within a grid cell. The length of edge segments was calculated after a Canny edge detection algorithm (Canny, 1986; National-Instruments, 2005) was applied. The first feature, the distance to the crop row (*a*), was used for the context adaptive training of the classifier. The other five features were used for the multivariate Bayesian classification. Two classes were trained: volunteer potato and sugar beet.

For both the sugar beet class and the volunteer potato class, training feature vectors were stored in a buffer of 100 grid cells based on the following function to determine training candidate grid cells (Equation 4.2), where σ is the variance of the crop row width, and *a* represents the distance to the center of the crop row:

$$\mathrm{f}(a) = \left\{ \begin{array}{ll} a < 1\,\mathrm{cm} & \Rightarrow \text{Sugar Beet training candidate} \\ 1\,\mathrm{cm} < a < 1.5\sigma\ \mathrm{cm} & \Rightarrow \text{To be classified} \\ a > 1.5\sigma\ \mathrm{cm} & \Rightarrow \text{Volunteer Potato training candidate} \end{array} \right\} \tag{4.2}$$

Two first-in-first-out (fifo) buffers were used. One for the sugar beet training data and one for the volunteer potato training data. Using a fifo-buffer means that the oldest information is pushed out, when newer training data of vegetation was available. The buffers were implemented as follows:

{ For m new training grid cells G

For i=0 to 99-m

$B[100\text{-}i] = B[100\text{-}(i+m)]$ (shift and remove oldest data, 'First Out')

For i=1 to m

$B[i]=G$ *}* (insert new training grid cell features, 'First In')

Where B is a buffer of 100 grid cell feature vectors, i is the position in the buffer B, and m is the number of grid cell feature vectors that is added to the buffer B. When both buffers were filled with training data of 100 grid cells, the a priori training data was available. Then, the feature values were normalized by subtracting the mean and dividing by the standard deviation. Subsequently, covariance matrices and mean vectors were calculated from the buffer as a priori data for classification. A multivariate Bayesian statistical classifier was used as described in Gonzalez and Woods (1992) (Equation 4.3)

$$d_j(x) = \ln P(\omega_j) - \frac{1}{2}\ln\left|C_j\right| - \frac{1}{2}\left[(x - m_j)^T C_j^{-1}(x - m_j)\right] \tag{4.3}$$

$d_j(x)$ is the value of the decision function for class j

$P(\omega_j)$ is the prior chance for class j

C_j is the covariance matrix for class j

$x - m_j$ is the feature vector x – mean feature vector for class j

j is 1 or 2, volunteer potato and weeds or sugar beet

Then, the values of the $d_j(x)$ functions for all the grid cells in the image were determined and a grid cell was classified in the class with the highest value for $d_j(x)$. Finally, the resulting images with classified grid cells were filtered with a low-pass filter size of 4 square centimeters to remove all small objects as these are too small to be sprayed within our research project.

We applied the Bayes classification in both an adaptive and a non-adaptive method. The non-adaptive classification was only trained at the start of the field until 100 vegetation grid cells for both the sugar beet and the volunteer potato class were available. Then the training was stopped, and the rest of the field was classified with the information gathered from the 100 vegetation grid cells. In the non-adaptive case, the crop row width was kept at the mean crop row width recorded until the 100 grid cells of training data was available. In the adaptive classification the training data was continuously updated in the fifo-buffer of 100 grid cells of sugar beet and volunteer potato plant along the travel through the field according to Equation 4.2. In both classification schemes, the calculated crop row position was always taken into account, as this also compensated for operator or driver inaccuracy between the measurement days.

Classification results were obtained for two measurement days that included the same crop row section of 50 m length. At 18-05-2006 (Day 1), the measurements were done with an overcast sky and constant natural lighting conditions. At 24-05-2006 (Day 2), the measurements were done during changing natural lighting conditions, with sunlit and overcast periods.

For the crop recognition images recorded during the two measurement days, ground truth images were created manually. One by one, grid cells were manually identified as volunteer potato plant or as sugar beet plant. The plants were separated from each other by hand as well, in a way that the number of sugar beet and volunteer potato plants that were present within the images could be counted. The creation of ground truth images is a crucial step for evaluation of machine vision algorithms (Thacker *et al.*, 2008). It is however not part of the final implementation of an algorithm in a practical situation. With use of the ground truth images, the validity of the features chosen for discrimination was determined. This was done by a linear discriminant analysis (SAS, 1989), as this analysis shows the contribution of the individual features to the discrimination between the two classes. Secondly, confusion tables and the classification accuracy of our algorithm are given and the causes for its performance increase or decrease are discussed when an adaptive or non-adaptive classification scheme was applied.

4.4 Results

Image quality

The quality obtained from the row and crop recognition images was good, in a sense that a constant threshold value of 10 could be used on the excessive green value to separate vegetation from the soil background. For the crop recognition camera the image intensity at the grey reference board was measured and is displayed in Figure 4.3. The camera hardware was programmed to maintain constant lighting conditions based on the grey reference in the field of view. Nevertheless, the camera could not always directly correct for quick changes in lighting intensity as shown by the peaks in the intensity of the reference for Day 2. Sometimes natural light conditions changed faster than the rate at which the camera grabbed images and could correct for changing light conditions. This was probably due to the hardware trigger that was used to grab images. The image recording speed was related to the travel velocity, which was a walking speed close to 1.0 m s^{-1}. Approximately two images per second were recorded, and so two times per second the camera hardware algorithm could change its shutter-time to compensate for changing light conditions. On Day 1, the natural lighting conditions were constant, and so the camera was able to keep a constant intensity of 128 at the reference board.

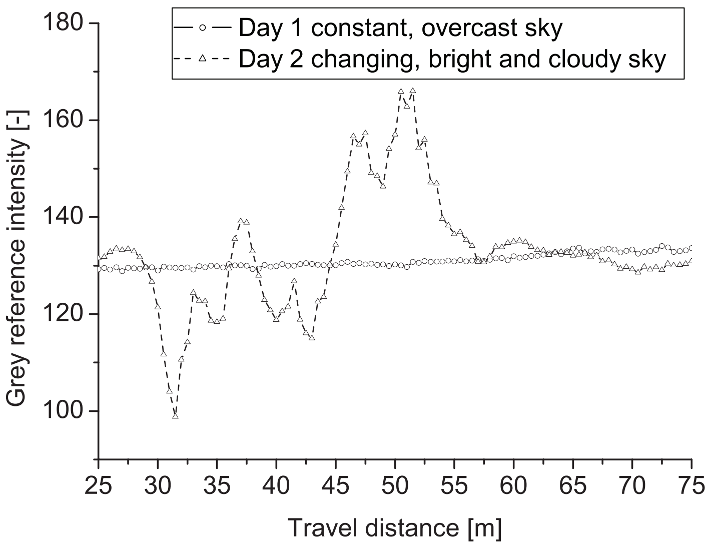

Figure 4.3 The grey reference intensity for an overcast sky at Day 1 and a bright and cloudy sky at Day 2.

Crop row detection and crop row width

When vegetation was thresholded from the background soil, the crop row position and the crop row width were determined. The crop row position that was determined related well to the actual crop row position, based on visual assessment as shown in Figure 4.2. Of course, the crop row position was not always exactly in the middle of the images, due to operator driving inaccuracy during the measurements but it was found at the correct position with regard to the real crop rows. Of higher importance for the training stage of the classifier was the crop row width as shown in Figure 4.4. The crop row width was larger at Day 2, because the plants were one week older and therefore larger in size. This means that the inter-row spacing area available for obtaining volunteer potato training data reduced with increasing growth stage. But also during one measurement day, considerable variations in crop row width could be observed. On Day 1, crop row width varied between 70 and 160 mm. During Day 2, the crop row width varied between 80 and 190 mm. These data show that differences up to 90 mm change in crop row width existed when the volunteer plants had to be detected. Adapting the crop row width to actual crop row width, maximized the area between the crop rows available for obtaining training data for volunteer plants according to Equation 4.2.

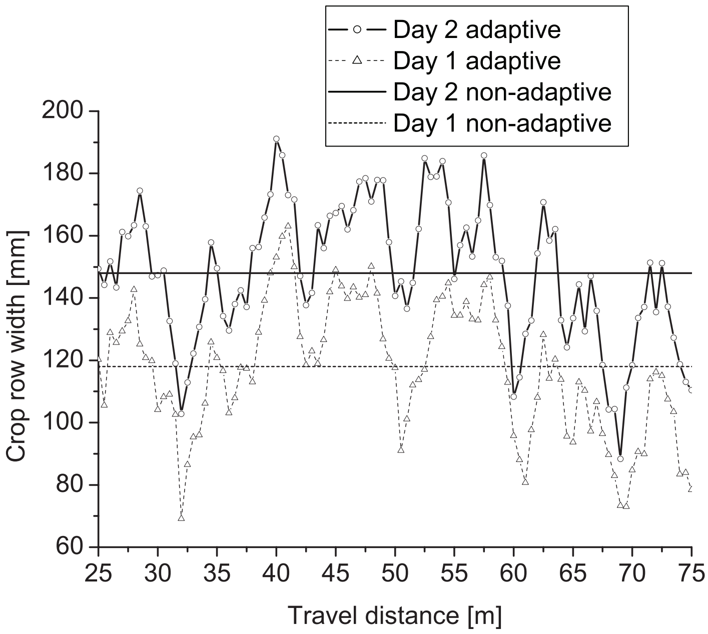

Figure 4.4 Crop row width [mm] as a function of travel distance [m] during the two experiments.

Feature quality / linear discriminant analysis

The discriminative power of the features used were identified with a discriminant analysis. This was possible through the use of the ground truth images of the sugar beet and volunteer potato grid cells. The features that the linear discriminant analysis selected, in order of magnitude of variance that they explained, is given in Table 4.1. From the features Red, Green, EG, RB and Texture at Day 1 only EG, Green, and RB were selected as discriminative. For the images of Day 2, EG, Green, Texture and RB were selected as discriminative features. When the natural light conditions were constant, the texture was not needed as a feature. In both situations, the red color feature was not selected as a discriminative feature by the stepwise selection method, as this feature did not reach the F value of 3.84 to be entered as a variable in the discriminant analysis.

Table 4.1 Stepwise selection method results of discriminant analysis to identify the importance of the features for their discriminative power. At each step the variable that reduced the variance most was entered into the analysis

	Day 1		Day 2	
Step	Entered	Residual variance	Entered	Residual variance
1	EG	0.173	EG	0.622
2	Green	0.089	Green	0.428
3	RB	0.087	Texture	0.401
4			RB	0.393

The feature mean values and variances within the experiments are given in Table 4.2. The variances of the feature values were larger at the second measurement day when the natural lighting conditions were more variable. The intensity of the reference board, which was the constant factor between experiments, showed an increase of variance from 1.97 to 147.26 between the two measurement days; proof that the camera could not maintain the desired intensity value of the grey reference board.

Table 4.2 Feature mean values and variances for the two measurement days. The features are ordered by the amount of variance that they explained, according to the linear discriminant analysis of Day 2.

	Day 1		Day 2	
	mean	variance	mean	variance
Intensity Reference	131	2	133	147
EG Sugar beet	20	<1	15	4
EG Volunteer potato	14	2	12	2
Green Sugar Beet	114	23	97	123
Green Volunteer Potato	98	37	95	57
Texture Sugar beet	42	6	45	9
Texture Volunteer potato	52	26	57	46
RB Sugar beet	41	1	32	16
RB Volunteer potato	30	5	29	13
Red Sugar Beet	119	28	102	134
Red Volunteer Potato	101	39	101	66

The color and texture features of the plants show an increased variance for the second measurement day with changing natural light conditions. During the first measurement day, when natural light conditions were constant, the variances of the volunteer potato plants were larger compared to the sugar beet plants.

In more detail, the EG feature value is shown in Figure 4.5. The EG feature value explained the largest amount of variance and was therefore chosen to demonstrate the evolution of the feature values while travelling over the field over a distance of 50 m. During the first measurement day, under constant natural light conditions, the EG feature value varied considerably. As the natural light conditions were constant, this indicates an intrinsic color change of the plants within the field.

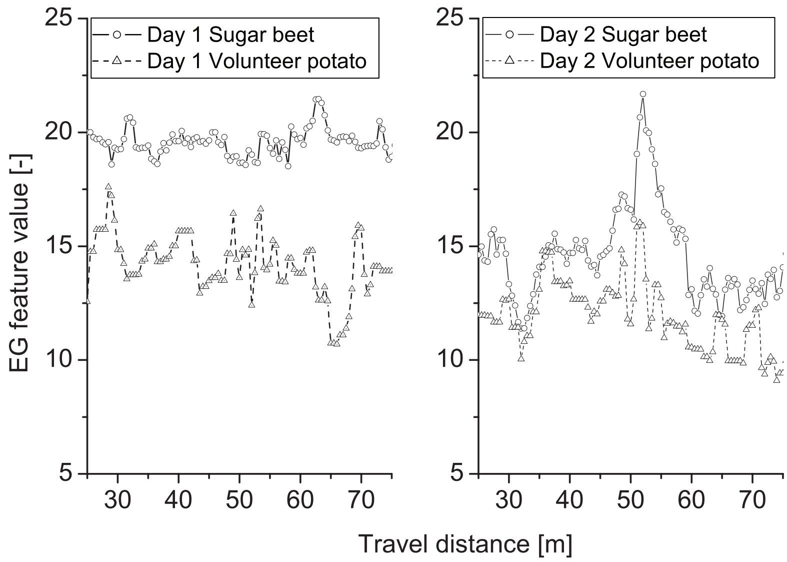

Figure 4.5. The EG feature values of the sugar beet and volunteer potato plants on the two measurement days plotted against the travel distance.

On Day 2, when the natural light varied during the experiment, the EG feature value as shown in Figure 4.6 changed similarly to the reference intensity as seen in Figure 4.3, showing a peak at 50 m travel distance. On Day 2, changes in EG feature value cannot completely be attributed to the intrinsic crop color changes, as the recording conditions were not constant. On Day 2 the intensity of the images was not constant, therefore the EG feature values of the plants were not separated, but got mixed along the travel distance through the field as shown in Figure 4.6.

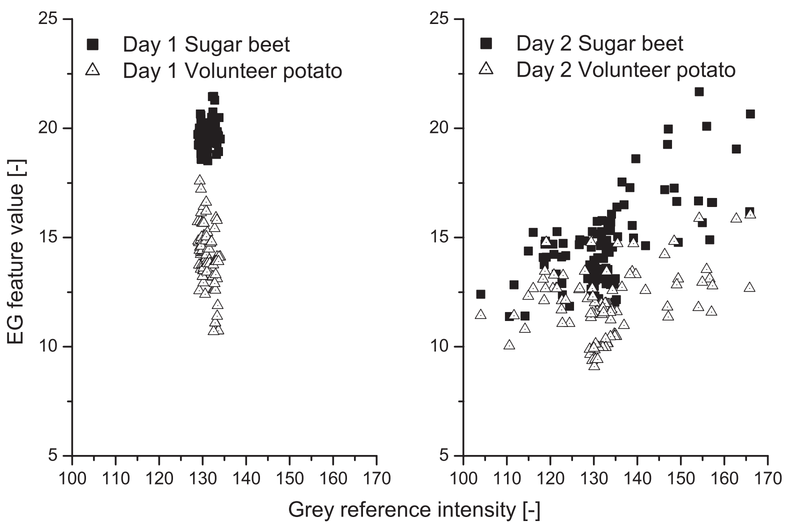

Figure 4.6 The EG feature values of the sugar beet and volunteer potato plants on the two measurement days plotted against the grey reference intensity.

Classification accuracy

The classification results were judged against the ground truth images and the percentages of classified plants are shown in Table 4.3.

Table 4.3. Classification results for sugar beet and volunteer potato plants at Day 1 and Day 2 for non-adaptive and adaptive Bayes classification. In bold the classification accuracy is given. VP = Volunteer potato; SB = Sugar beet. True positive, false positive, false negative and true negative percentages of classified plants are shown. The number of plants is shown in the column marked with #.

	Day 1					Day 2			
Not adaptive									
		Result					Result		
	84.6	VP	SB	#		**34.9**	VP	SB	#
Groundtruth	VP	98.6	1.4	72	Groundtruth	VP	98.5	1.5	66
	SB	20.2	79.8	213		SB	85.4	14.6	206
Adaptive									
		Result					Result		
	89.8	VP	SB	#		**69.7**	VP	SB	#
Groundtruth	VP	100	0	72	Groundtruth	VP	90.6	9.4	64
	SB	13.6	86.4	213		SB	36.7	63.3	207

Classification accuracy is the percentage of correctly classified sugar beet and volunteer potato plants combined. For the data of Day 1, this resulted in a classification accuracy of 84.6% when the static, non-adaptive Bayes classification was applied. On the other hand, the classification accuracy was 89.8% when the Bayes classification was adaptive. On Day 1 the SB misclassification reduced from 20.2% to 13.6% as a result of the application of the adaptive classification scheme. The data from Day 2 gave 34.9% classification accuracy for the non-adaptive Bayes classification. The adaptive Bayes classification had an accuracy of 69.7%. On Day 2 the SB misclassification reduced from 85.4% to 36.7% as a result of the application of the adaptive classification scheme. At both measurement days the adaptive algorithm had a better classification accuracy, indicating that adapting to local plant color and texture features increased classifier performance.

An example of a classified volunteer potato plant within a sugar beet crop row is given in Figure 4.7. The classification result in Figure 4.7b shows that centimeter precision of classification was feasible within the crop row. The red color represents a volunteer potato plant, green color represents a sugar beet plant.

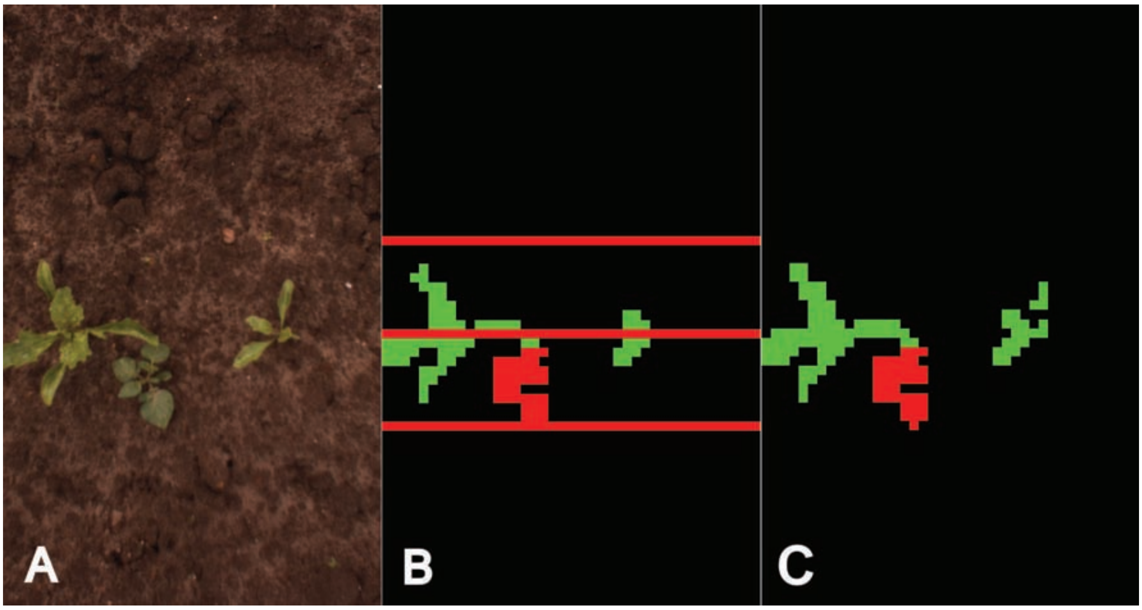

Figure 4.7. Original image (A) and classification result of a volunteer potato plant (B) within and between sugar beet crop rows. (C) Shows the ground truth of the same image that was created by hand. Each block represents 100 mm^2.

4.5 Discussion

Image quality and vegetation separation

Apparently our triggered acquisition frame rate of 2 Hz was too low to adjust the camera shutter-time fast enough to changing natural light conditions in the field. This was shown by the changing grey reference board value in Figure 4.3. Tillett and Hague(1999) reported that their acquisition frame rate was 25 Hz, which means that their setup could adjust to changing conditions 12.5 times per second more than our setup. However, if the frame rate of our camera was increased, redundant data would have been recorded as the image scene itself would not have changed completely before a new image was recorded. On the other hand an increased frame rate would provide data for faster adaptation to intensity changes as well, and improve the classification results. This would reduce the interference of EG values between sugar beet and volunteer potato plants as seen in Figure 4.6. Our vegetation separation was based on a constant threshold on the excessive green. During the data analysis no problems occurred using the constant threshold for vegetation separation, however Meyer and Camargo Neto (2008) showed that an excessive green minus an excessive red outperformed the traditional excessive green classifier for vegetation detection. This could be an improvement when problems arise with vegetation separation in future research. In our setup no problems appeared with shadows in our images. However it could happen under natural light conditions that shadows become a problem for correct color classification. Marchant and Onyango (2000) reported a shadow invariant transformation to overcome the problems of shadows in images with vegetation that could be implemented in our work as well. Another solution to shading and intensity interference could be a covered measurement setup with controlled light conditions.

Crop row recognition and crop row width

The crop row recognition was not validated with help of ground truth images. The crop row positions however do determine which data is used for training of the classifier. In that way the crop row recognition is a crucial step in the performance of the classifier, either adaptive or static. Since our algorithm is based on Tillett and Hague (1999), the row recognition errors will be in the same range of 13 to 18 mm. Bakker *et al.* (2008) reported errors of row recognition with a Hough transform algorithm between 5 and 11 mm. Both Tillett and Hague (1999) and Bakker *et al.* (2008) do not report on the dimensions of the crop row width, although crop row width and growth stage are important parameters for weed detection and weed control systems as well. Tellaeche *et al.* (2008) reported a vision based algorithm that takes into account the crop growth stage for weed detection as well. However the precision of their algorithm was not reported, but was estimated to be larger with a value of 0.1 m^2. In that way our algorithm for square centimeter precision weed detection is an improvement over existing algorithms reported in literature, taking into account the crop row position and width.

Feature quality

The linear discriminant analysis for evaluation of the features used a stepwise selection procedure to identify the valuable features. However, the Bayes classifier itself was a multivariate classifier, taking into account all the five color and texture features. The efficiency of the multivariate classifier could be improved with an automatic feature selection process. Examples of these are principle components based classifiers, or automatic feature selection processes as explained in Maenpaa *et al.* (2003). The linear discriminant analysis was done on the complete data set available from the ground truth images. The Bayes classifier however, was used only on the local features that were stored in the buffer of 100 vegetation grid cells. Therefore, it could be that locally some features are more discriminative than others. This can explain some of the differences between the features that were selected at Day 1 and Day 2 as well. The lighting conditions were different at Day 2. Therefore the colors recorded will be different, and the texture feature was needed as well to discriminate between volunteer potato and sugar beet. Another valuable feature that could further increase the discriminative power between the weed potato and sugar beet class are the near-infrared reflection properties of the vegetation. Gerhards *et al.* (2002) mention that the near-infrared reflection properties of weeds and crops can help in distinguishing between them.

Adaptive and non-adaptive classification

Local multivariate normal distributions were used to discriminate between volunteer potato and sugar beet plants. When the classifier was applied non-adaptively, the training data at that point in the field determined the classification accuracy later on in the field. Our data showed that crop features like crop row width, color and texture, change throughout the field, and therefore adaptive classification outperformed non-adaptive classification. It took into account the changing crop row width, the actual crop color and texture, and could adapt to changing natural light conditions. This adaptive behavior was feasible through the buffer of grid cells with vegetation features that was stored. The size of the buffer of 100 grid cells was chosen because it represented the size of about five sugar beet plants. Obviously one could reduce adaptive behavior by increasing the buffer of stored vegetation features, thereby increasing the standard deviations of the multivariate normal distributions represented in the covariance matrices from Equation 4.3. The classification results from Table 4.3 showed that the adaptive scheme resulted in lower percentages of misclassification of sugar beet. This is even more important than an increase in classification accuracy, as the actuator will eventually spray a non-specific herbicide on all the grid cells that were identified as volunteer potato.

General

For a static classifier it is necessary to choose training data in advance, although choosing representative training candidates for changing and different field situations can be difficult (Nieuwenhuizen *et al.*, 2007). The progression made to other research is that the adaptive Bayes classification as used in this research showed that using actual context information improves classification results like the context based methods proposed by Astrand (2005). Furthermore, the drawbacks of having to choose training data in advance are not valid anymore, as online training data is always available by using the crop row position for choosing training data progressively.

4.6 Conclusion

In this research, an adaptive Bayesian classification method has been developed for classification of volunteer potato plants within a sugar beet crop. Crop row information was successfully used to train the adaptive classifier without having to choose training data in advance. Adaptive classification, taking into account the crop growth stage, and the local crop and volunteer potato color and texture features, increased classification accuracy.

1) Automatic classifier training is feasible. The only information needed is that one crop row position has to be detectable and its row width can be determined. The crop row width changes within a field for many agronomic reasons, e.g. growth conditions, pests, diseases. Therefore, adapting to the crop growth stage increases availability and quality of training data of the classifier.

2) The features needed for detection were EG, green, RB, and texture. These features were selected with a stepwise selection method followed by a linear discriminant analysis. Changing light conditions required one extra feature, in this case texture. Texture was not needed under constant natural light conditions.

3) With use of ground truth images, the classification accuracy of the plants was determined. In the non-adaptive scheme the classification accuracy was 84.6% and 34.9% for the constant

and changing natural light conditions respectively. In the adaptive scheme the classification accuracy increased to 89.8% and 67.7% for the constant and changing natural light conditions respectively, thus supporting the adaptive classification scheme.

4.7 Acknowledgements

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Chapter 5

Real-time unsupervised adaptive Bayesian classification for weed plant detection in arable fields

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5.1 Abstract

Disease pressure from volunteer potato plants and its high requirements on labor, energy and chemicals for the control of the weed potato plants urge for an automated detection and control system. This work addresses an unsupervised real-time adaptive algorithm for colour feature based classification of square centimeter vegetation grid cells of sugar beet and volunteer potato plants. A row detection algorithm and a Kalman filter were used to track rows and to determine the crop row width. Subsequently, a multivariate Bayes classifier was trained adaptively in a ‘first in first out’ manner. The highest classification performance was 96.6% for volunteer potato and 8.0% misclassification for sugar beet plants on one field. The features blue, hue, saturation, excessive green, red minus blue, near infra-red, and NDVI were of discriminative power, whereas the features red, green, and intensity did not contribute much to the classification. During the classification the Mahalanobis and Fréchet distance between multivariate distributions were calculated to predict the Bayes classification performance. The Fréchet distance was preferred as quality indicator for the classification, as it had a smaller standard deviation compared to the Mahalanobis distance. In the largest growth stage, a travel velocity of 1 m s^{-1} was achieved, as the calculation time for an image with a length of 20 cm length was 195 ms. In smaller growth stages travel speed might be increased as less computation is needed on green vegetation. A robust real-time detection system has been created that forms the basis of an integrated system to control volunteer potato plants.

5.2 Introduction

Volunteer potatoes are a major problem in crop rotation in Dutch arable farming (Askew & Struik, 2007). These potato plants start growing as weeds from the remains of previous cropping and harvesting of potatoes in the autumn. Volunteer potatoes growing in other crops like sugar beet are a severe problem because they are the source of diseases and pests like *Phytophthora Infestans* and cause harmful nematodes to increase their population (Lutman, 1986). Because of these negative effects, Dutch legislation requires removal of weed potatoes during the growth season before the 1st of July. Some conventional broadcast spraying against weeds suppress the volunteer potato plants as well, but they are not completely controlled and re-growth will occur (Smid & Hiller, 1981). Until present, manual plant specific application of glyphosate is used to kill shoots and tubers of these plants. However, the increased costs of labor and an increase in arable farm area urged for an automated method for volunteer potato detection and removal, to ensure that the spread of diseases is decreased to a minimum and that the economic position of Dutch potato cropping is secured (Paauw & Molendijk, 2000).

For weed detection purposes many other studies were done in the past decade. However, either the relative resolution/precision of detection was low and the ground travel speed was high (Gerhards & Christensen, 2003; Telllaeche *et al.*, 2008), or the resolution/precision of detection was high but the travel speed was low and the algorithms were only executed off-line or in lab situations (Astrand & Baerveldt, 2002; Onyango & Marchant, 2003; Sogaard *et al.*, 2006). In this research a square centimeter resolution is required at a reasonable travel speed of at least 5 km h^{-1}.

This work addressed the technical challenges of a real-time machine vision based volunteer potato detection system and demonstrated the technology under field conditions. In the starting phase of the project in 2006, a set of requirements for the system has been defined in cooperation with farmers and machinery industry involved in the research. The requirements for the detection system were: 1) driving and working velocity between 1.5 and 2.0 m s^{-1}; 2) detection rate of volunteer potato plants better than 95%; 3) misclassification rate of sugar beet plants smaller than 5%; 4) detection within the crop row at square cm resolution. Several steps were done in the development of detection algorithms for volunteer potatoes in arable crops in variable outdoor conditions e.g. (Nieuwenhuizen *et al.*, 2007b). The vision based detection was further extended with controlled light conditions and a field of view above three crop rows in Nieuwenhuizen *et al.* (2008). However, the algorithm did not perform in real-time situations yet, and the quality of classification was only determined on a 50 m section on an experimental field. In this research, the algorithm of Nieuwenhuizen *et al.* (2008) was further improved by including an adaptive row tracking algorithm, real time implementation,

and an unsupervised quality indicator of classification. With the improved algorithm the following research questions were addressed:
- How can the detection algorithms be implemented in real-time software?
- What is the classification accuracy on fields with different soils and growth stages?
- How can the quality of classification be predicted in real-time for user feedback?
- Can the requirements be achieved with the developed research system?

5.3 Materials and Methods

Imaging hardware and software

The platform used for real-time imaging is shown in Figure 5.1. The height could be adjusted and flaps on the sides prevented shades and sunlight under the cover.

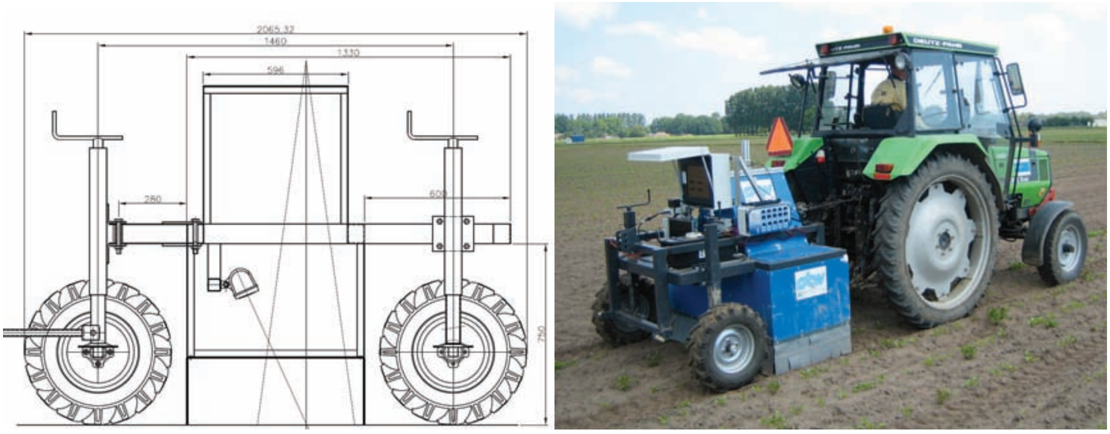

Figure 5.1 Imaging setup, (left) a schematic diagram with camera C and lamps L, (right) as used in the field attached to a tractor.

Two cameras were used, one color camera (Marlin F201c, AVT, Stadtroda, Germany) and a black and white camera (Marlin F201b, AVT, Stadtroda, Germany) that was fitted with a visible light block filter (IR longpass, 780nm 40.5 mm, LP780) to measure light reflectance in the near infrared wavelengths. The fields of view of the cameras covered a ground surface area of 150 cm width and 20 cm length (1628*198 pixels). The camera recordings were triggered with an optical wheel encoder that was connected to a field programmable gate array (FPGA) (NI-7831R, National Instruments, Austin, TX, USA). Furthermore, controlled light conditions were created using five Xenon lamps – regular work lamps as used on tractors – that were placed under the blue cover of the machine. Before the experiments were started, the colour balance of the camera was fixed based on a 50% grey reflection card (Fotowand, Technic, Sudwalde, Germany). The images were processed on a 2.2 GHz single core real-time computer (PXI-8096RT, National Instruments, Austin, TX, USA).

Pseudo code adaptive classification algorithm

The code processed each image in real-time. The travel speed during the experiments was 1.0 m s^{-1} maximum. A maximum of 200 ms was thus available to process each image as the length of the image in the travelling direction was 20 cm.

The classification procedure of the images contained the following steps:

1) *Preprocess image, illumination correction and Bayer decode*
2) *Create vegetation grid cells of 1 cm^2 in crop recognition image*
3) *Determine crop row positions and crop row widths, with Kalman filter*
4) *Determine feature values for each vegetation grid cell*
5) *Update a priori training data for classification*
6) *Normalize the feature values*
7) *Classify each grid cell with Bayes classifier and decide spray locations*

Image preprocessing

Some preprocessing steps were needed on the raw camera images before they could be processed in the detection algorithm. Preprocessing consisted of illumination correction and colour decoding. An illumination correction was necessary since the illumination from the Xenon work lamps was not uniform in the field of view of the cameras (Figure 5.2).

Figure 5.2 Calibration image for illumination correction in the image preprocessing.

Figure 5.3 Colour image after illumination correction.

After the illumination correction, the RGB camera images were Bayer decoded (Bayer, 1976) into colour images. Images from the NIR camera were only corrected for illumination.

Vegetation detection

Vegetation was detected in the images using an excessive green threshold (Woebbecke *et al.*, 1995). The excessive green value of a color pixel (EG) is calculated as $EG = 2 * G - R - B$ where G, R, and B are the green, red, and blue pixel values respectively. The corresponding decision for vegetation / soil background discrimination was based on examining multiple histograms and thereby minimizing the interclass variance. When the EG value > 15 the pixel was identified as vegetation, when the EG value ≤ 15 the pixel was identified as soil background. When more than 70% vegetation was found in a cell of 1 cm^2, this cell was identified as having green vegetation. Further calculations were based on the vegetation grid cells only, to reduce computation time.

Figure 5.4 Vegetation after thresholding on the excessive green value.

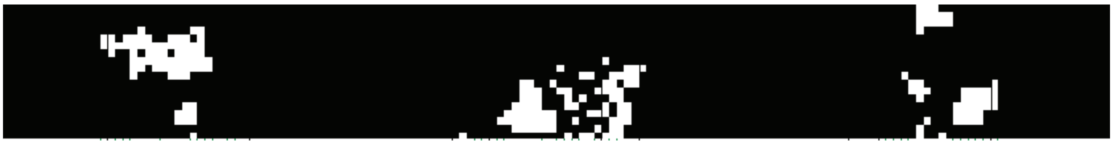

Figure 5.5 Vegetation grid cells of 1 cm^2 containing more than 70% vegetation.

Histogram based crop row detection and identification with discrete Kalman filter

Sugar beets are seeded with an inter-row distance of 50 cm. Therefore, in our setup three sugar beet rows could be detected in each 20 cm length image with a histogram based approach comparable to the technique used by Hague and Tillett (2001). Because large amounts of vegetation grid cells were situated at places within the seeding line, three peaks were found that corresponded to the crop rows (Figure 5.6).

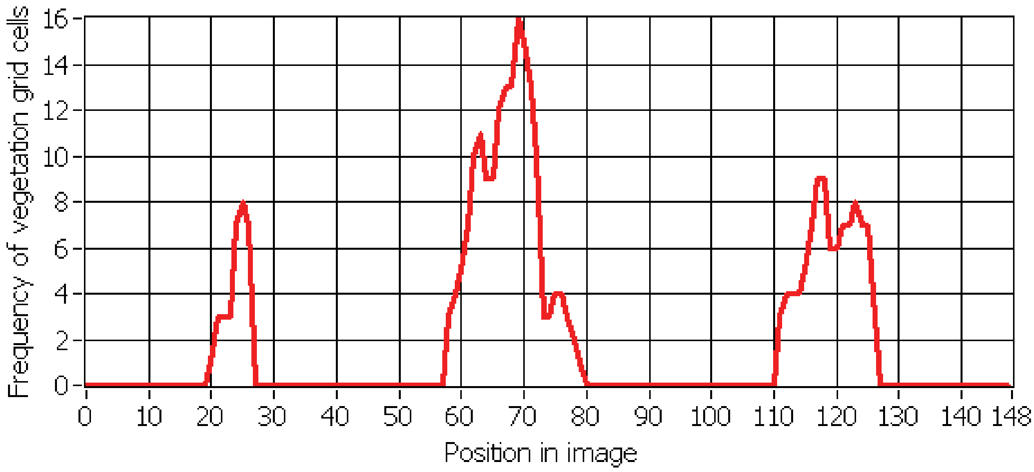

Figure 5.6 Histogram of vegetation grid cells within one image

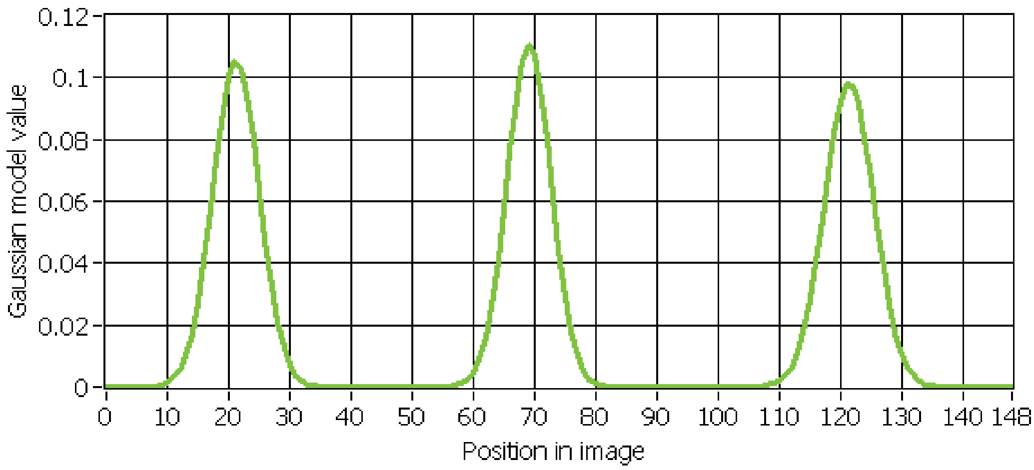

Figure 5.7 Fitted Gaussian bell shapes on the histogram of vegetation grid cells. Mean and standard deviation of normal distribution represents row position and row width.

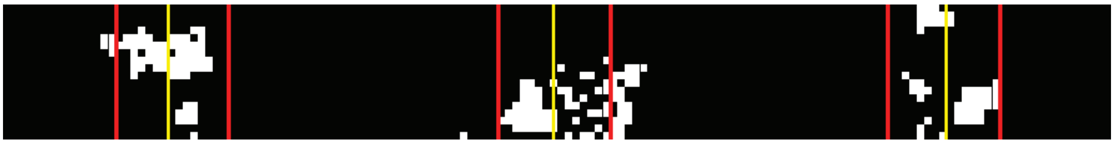

Figure 5.8 Row detection results overlaid on the vegetation grid cells image. The yellow lines represent the crop row position, the red lines represent the crop row width.

However, due to irregular growth of plants and weeds in an arable field and due to irregular driving a Kalman filter (Gelb *et al.*, 1974; Welch & Bishop, 2006) was used to filter the crop row positions and their width. The crop row width was described using the standard deviation σ of the assumed normal distribution of the frequency of the vegetation grid cells along the width of the three crop rows (Figure 5.7). Specifically, a discrete Kalman filter was used to estimate the crop row position and crop row width in the state $x \in \Re^n$ of the discrete process of image recording according to the following linear stochastic equations:

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \tag{5.1a}$$

with a measurement $z \in \Re^m$ that is

$$z_k = Hx_k + v_k \tag{5.1b}$$

The random variables w_k and v_k represent the process and measurement noise, in this application consisting of variations in curvature of the seeding line together with growth stage changes as well as variations due to incorrect driving of the machine over the crop rows. Process and measurement noise were assumed to be independent, white, and normally distributed $p(w) \approx N(0, Q)$, $p(v) \approx N(0, R)$ and were represented with the matrices Q and R. The filter equations and parameters are described in the following section. For each new image, the time update equations were computed with:

$$\begin{aligned} \hat{x}_k^- &= A\hat{x}_{k-1} + Bu_{k-1} \\ P_k^- &= AP_{k-1}A^t + Q \end{aligned} \tag{5.2}$$

And the measurement update equations were computed for each new image with:

$$\begin{aligned} K_k &= P_k^- H^t \left(HP_k^- H^t + R\right)^{-1} \\ \hat{x}_k &= \hat{x}_k^- + K_k\left(z_k - H\hat{x}_k^-\right) \\ P_k &= \left(I - K_k H\right)P_k^- \end{aligned} \tag{5.3}$$

Where the following definitions hold:

$\hat{x}_k^-$ is the a priori state estimate $[rp_1, rp_2, rp_3, rw_1, rw_2, rw_3]$ with rp_i and rw_i the row position and the row width of row *i* respectively, not taking into account the measurements of the current image,

$\hat{x}_k$ is the posterior state estimate $[rp_1, rp_2, rp_3, rw_1, rw_2, rw_3]$ with rp_i and rw_i the row position and the row width of row *i* respectively, taking into account the measurements of the current image,

A relates the state at the previous time step k-1 to the state at the current time step k,

H relates the state to the measurements z_k,

I is the identity matrix,

B relates the optional control input u to the state,

u is the vector with steering values to control the process,

P_k^- is the a priori error covariance matrix,

P_k is the posterior error covariance matrix,

K_k Kalman gain matrix,

z_k is the measurement vector $[rp_1, rp_2, rp_3, rw_1, rw_2, rw_3]$ with rp_i and rw_i the row position and the row width of row *i* respectively,

R is the measurement noise matrix,

Q is the process noise matrix,

and parameters are initialised as:

$\hat{x}_{k=0}$ = state estimate $[rp_1, rp_2, rp_3, rw_1, rw_2, rw_3]$ = $\begin{bmatrix}0.25 & 0.75 & 1.25 & 0.05 & 0.05 & 0.05\end{bmatrix}$ at k = 0,

A, H = I,

B, u = 0, as no steering was applied to control the process,

$P_{k=0}$ = I,

R = diag (R) $\begin{bmatrix}0.01 & 0.01 & 0.01 & 0.01 & 0.01 & 0.01\end{bmatrix}$,

Q = diag (Q) $\begin{bmatrix}1\cdot10^{-5} & 1\cdot10^{-5} & 1\cdot10^{-5} & 1\cdot10^{-5} & 1\cdot10^{-5} & 1\cdot10^{-5}\end{bmatrix}$.

The fixed measurement variance matrix R shows the uncertainty in the measurements which was estimated at 1 cm. The process variance was fixed at a factor 1000 smaller than the measurement variance. This resulted in a balanced responsiveness and estimate of the variance on the estimates of row position and row width.

The feature vector for each grid cell

Ten features were calculated for each grid cell that contained vegetation. These features were (1) mean red, (2) mean green, (3) mean blue, (4) mean hue, (5) mean saturation, (6) mean intensity, (7) mean excessive green, (8) mean red minus blue, (9) mean near infra-red, and (10) mean NDVI. The mean red, green, and blue values were calculated directly from the colour vegetation pixels within the grid cell. The mean hue, saturation, and intensity values were calculated after the conversion of RGB to HSI according to Gonzalez and Woods

(1992). The mean excessive green and mean red minus blue were calculated according to Steward *et al.* (1999) with:

$$\begin{bmatrix} EG \\ RB \\ I \end{bmatrix} = \begin{bmatrix} \frac{-1}{\sqrt{6}} & \frac{2}{\sqrt{6}} & \frac{-1}{\sqrt{6}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{-1}{\sqrt{2}} \\ \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{5.4}$$

where

EG = Excessive Green,

RB = Red minus Blue,

I = Intensity.

This transformation is a rotation of the RGB coordinate vectors such that the resulting I-coordinate is collinear with the intensity axis. The EG and RB coordinates span a colour plane with in one direction the greenness and perpendicular to that values ranging from blue to red.

The mean near infra-red was calculated directly from the vegetation pixels within the grid cells of the nir-camera. Finally, the mean near infrared difference vegetation index (NDVI) was calculated as (*nir-red*)/(*nir+red*) (Thorp *et al.*, 2004).

Update of the classifier training data

When the crop rows were identified and the feature values of the grid cells were available, training data for the classifier could be gathered. Vegetation grid cells located in the crop rows were used as sugar beet training data. Data outside the crop rows was used as volunteer potato training data, explained in Equation 5.5. This scheme was applied until data of 500 grid cells of each class was gathered.

$$f\left(y, rp_i, rw_i\right) = \left\{ \begin{matrix} InRow & if \quad rp_i - 1.96rw_i < y < rp_i + 1.96rw_i \\ OutOfRow & else \end{matrix} \right\} \text{ with } i\text{=1,2,3} \tag{5.5}$$

Equation 5.5 gives the training data function. Whether a grid cell was used as sugar beet or volunteer potato training data was decided based upon the lateral y-position of the grid cell with regard to the crop row position and width. The width of the crop row was multiplied with a factor 3.92, as in a normal Gaussian distribution 95% of the data is within 3.92σ. This guaranteed that 95% of the vegetation of the sugar beets was within the crop rows and a maximum of 5% of the sugar beet vegetation was trained as volunteer potato. This maximized the quality of the training data of both classes. Once 500 grid cells for each class had been gathered, the feature values were normalized by subtracting their mean value and dividing by their standard deviation.

Adaptive Bayesian classification

The Bayes classifier is based on the principle of Bayes decision theory which provides a methodology for solving statistical classification problems when the probability distribution of the pattern is known. The Bayes classifier uses a probabilistic approach to assign a feature vector to a certain class (Gonzalez & Woods, 1992). In this research C denotes a class from the set of two classes (C_1 and C_2) and F_k is a sample described by a feature vector $F_k = [f_1, f_2, \ldots f_k]$. The Bayes classifier computes the posterior conditional probability $P(C_i \mid F_k)$ using Bayes' rule $P(C_i \mid F_k) = \frac{P(C_i)P(F_k \mid C_i)}{P(F_k)}$ for i = 1, 2, …, n. In the equation $P(F_k \mid C_i)$, $P(C_i)$, and $P(F_k)$ are calculated using training data. According to Bayesian theory, for a given observation F_k, one predicts a class for which the posterior probability is maximum: $f(F_k) = \arg\max_i P(C_i \mid F_k)$.

When multivariate normal distributed features are assumed, the probability density of a k-dimensional sample for a given class C_i is given by

$$P(F_k \mid C_i) = \frac{1}{(2\pi)^{k/2}|\Sigma_k|^{1/2}} \exp\left(-\frac{1}{2}(F_k - \mu_k)\Sigma_k^{-1}(F_k - \mu_k)^t\right) \tag{5.6}$$

Introducing the multivariate normal probability density function into Bayes' rule, taking a 0-1 loss function and taking the natural logarithm, yields the multivariate decision function:

$$d_i(F_k) = \ln P(C_i) - \frac{1}{2}\ln|\Sigma_i| - \frac{1}{2}\left[(F_k - \mu_i)^t \Sigma_i^{-1}(F_k - \mu_i)\right] \tag{5.7}$$

with

$P(C_i)$	= prior chance for class *i*,
Σ_i	= covariance matrix for class *i*,
$F_k - \mu_i$	= feature vector F – mean feature vector for class *i*,
i	= 1 or 2, volunteer potato and weeds or sugar beet, respectively.

The pattern vector F_k is assigned to the class whose decision function yields the largest numerical value. After classification, the training data was updated. Only the grid cells that were classified as sugar beet were input to the sugar beet training data. The volunteer potato training data was updated with all the vegetation found outside the rows. Both classes were updated with a 'first-in-first-out' buffer of 500 vegetation grid cells. Then, new covariance matrices and mean vectors were determined that could be used for classification of grid cells of the next image. The prior chances for the sugar beet and volunteer potato class were fixed and set at 98% and 2% respectively, based on examining experimental data of 2007. When grid cells were classified, small plant objects were filtered. This was done because volunteer potato plants with an area (A) smaller than 12 cm^2 have insufficient uptake of herbicides (Devine *et al.*, 1993). Filtering was done according to Equation 5.8.

$$f(A) = \begin{cases} \text{Classify} & \text{if} \quad A \geq 12 \\ \text{Remove} & \text{if} \quad A < 12 \end{cases} \tag{5.8}$$

Unsupervised expected quality of classification

The classifier was trained based on information from the row recognition algorithm. It was not trained on humanly labeled examples. Therefore, the system is an unsupervised classification system, with only the distance between the crop rows -50 cm- being input in the algorithm. As such, there is no guarantee that the trained classes within the Bayes classifier will give a good performance. It was therefore envisaged that a separate quality parameter should be introduced to inform the user of the expected quality of classification of the Bayes classifier. When quality was expected to be too low, the actuator connected to the detection system should be stopped and economic risks of misclassification might thus be minimized. This is especially important as the proposed actuator will work with glyphosate that kills all the vegetation. Within the classification procedure, two classes of multivariate data were available that were used to calculate a measure of expected classification quality. As a quality parameter, the distance between two multivariate normal distributions was calculated. The larger the distance, the better the classification results. This was implemented with the Mahalonobis and Fréchet distance (Dowson & Landau, 1982; Vergés-Llahí & Sanfeliu, 2005).

The Mahalanobis distance is the squared distance between a sample point y and a distribution X and is computed as:

$$D^2(y, X) = (y - \bar{x})\Sigma_x^{-1}(y - \bar{x})^t,$$

and the other way around between x and Y:

$$D^2(x, Y) = (x - \bar{y})\Sigma_y^{-1}(x - \bar{y})^t,$$

which can be combined into:

$$D^2(X, Y) = \frac{1}{2}\left(D^2(\bar{x}, Y) + D^2(\bar{y}, X)\right),$$

and results in the measure between two distributions as:

$$D^2(X, Y) = (\bar{x} - \bar{y})\left[\frac{1}{2}\left(\Sigma_x^{-1} + \Sigma_y^{-1}\right)\right](\bar{x} - \bar{y})^t \tag{5.9}$$

where Σ_i is the covariance matrix of class i.

The Fréchet distance is composed of two terms, an Euclidean distance measure among means and a distance on the space of the covariance matrices and is defined as:

$$D^2(X,Y) = \|\bar{x} - \bar{y}\|^2 + tr\left[\Sigma_x + \Sigma_y - 2\left(\Sigma_x \Sigma_y\right)^{1/2}\right] \quad (5.10)$$

where Σ_i is the covariance matrix of class *i* and where *tr* stands for the trace of the matrix. The two distance measures were calculated for each image when new training data was added to the training data buffer. The mean values and standard deviations of both distance measures are presented for the experiments done in 2008.

Experiment and data analysis with ground truth

Apart from the real-time Bayes classification procedure used in the experiments, a discriminant analysis was done to evaluate the quality of the features that were used.

A stepwise selection method (Discriminant Analysis, SPSS Inc., Chicago, IL, USA) was used to identify the variables that were responsible for the discrimination between sugar beet and volunteer potato vegetation grid cells. The F-values to enter and remove variables from the analysis were 0.05 and 0.10 respectively, based on explained variance.

Experiments were done in September 2007 and May and June 2008. Fields of 300 m^2 were seeded with sugar beets and volunteer potato plants were planted. In 2007 one sand soil field was used, in 2008 experiments were repeated on three days on a sand and clay soil, to improve the reliability of the classification results. When a suitable growth stage for detection and control was reached, the field was recorded. From the recorded images sugar beets and potato weeds were labeled off-line to be used as ground truth data. The ground truth data and the classification results were compared and expressed in confusion tables according to the following definition:

	Result VP	Result SB	Classification accuracy
Ground truth VP	TN	FP	$\left(\frac{TN+TP}{TN+FN+TP+FP}\right)$
Ground truth SB	FN	TP	

where TN is True Negative, FP is False Positive, FN is False Negative, and TP is true positive.

5.4 Experimental results and discussion

Row detection

The crop row detection results for 28-05-2008 on clay soil are shown in Figure 5.9. The figure shows that the Kalman filter was correctly initialized at 0.25, 0.75, and 0.125 m to find row positions. Soon, the histogram based approach identifies that the rows are more on one side of the machine because the tractor-machine combination did not travel exactly over the middle of the three sugar beet rows. After 10 m the error covariance was converged, and the filtered crop row positions reasonably followed the three crop rows. The spikes visible in the measured crop row positions are caused by volunteer potato plants that are positioned between or aside the actual crop row. These plants influence the mean position of the peak within the histogram, but the algorithm exhibits robust behavior in the face of these disturbances.

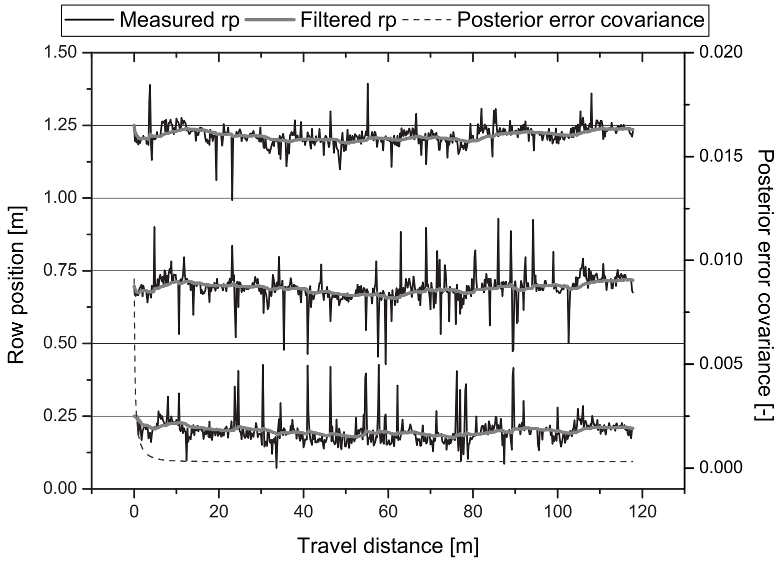

Figure 5.9 Measured row position (rp) and filtered row positions and the posterior error covariance at 28-05-2008 on clay soil as function of the travelled distance.

The crop row width of the middle crop row on 28-05-2008 on clay soil is given in Figure 5.10. The posterior error covariance was converged after 10 m, which equals 50 images. The standard deviation of the distribution that represented the crop row width was estimated around 4 cm by the Kalman filter. The measured row width distribution shows many peaks. However, the Kalman filter achieved a robust estimate of the crop row width. The spikes that were measured were again caused by volunteer potato plants that were growing between or within the sugar beet crop row. These local large crop row widths were filtered out, and as a result a better quality of training data was available for training of the classifier.

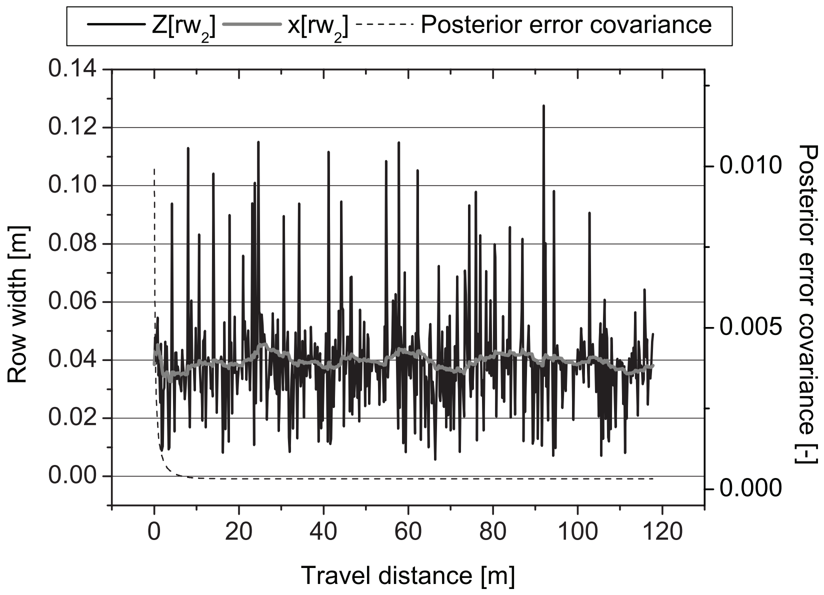

Figure 5.10 Measured row width of the middle row ($Z[rw_2]$) and filtered row width of the middle row ($x[rw_2]$) and the posterior error covariance at 28-05-2008 on clay soil as function of the travelled distance.

Training of the Bayes classifier

The data used for training was determined based on Equation 5.5. The interaction of crop row position and crop row width is graphed in Figure 5.11. Along the travel distance, the row positions and the crop row width were adapted to the local growth stage and position. The black areas within the crop row were used as training data for sugar beet plants, the grey areas were used as training data for volunteer potato plants. The positions of the three crop rows changed almost identical after the Kalman filter had converged. This agrees with the 50 cm distance that is between crop rows when they were seeded. The changes in crop row positions were either caused by a curvature in the seeding line or by not straight manual driving over the crop rows when the detection was done in the field experiment. However, this is not a problem as the algorithm itself adapted to the position of the crop rows and the corresponding crop row width.

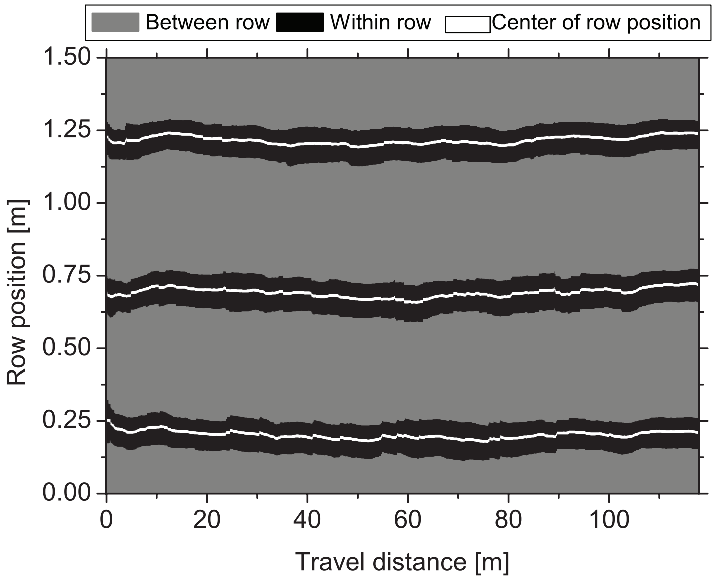

Figure 5.11 Row position and row width are given as a function of the travel distance. The black areas within the crop row were used as training data for sugar beet plants, the grey areas were used as training data for volunteer potato plants.

For a correct working Bayes classification algorithm, the prior probability $P(C_i)$ from Equation 5.7 is required for both classes. During the experiments $P(C_i)$ was set at 98.0% and 2.0% for sugar beet and volunteer potato plants respectively. These were based on experimental data of September 2007. For the experimental data in 2008 the occurrence of sugar beet and volunteer potato plant vegetation grid cells was calculated as well. However, this counting was done after the experiments, based on the ground truth images that were made. This was done to see if the estimate of the prior chances of 2007 was correct. The resulting percentages are given in Table 5.1. On average 96.1% and 3.9% vegetation grid cells occurred in sugar beet and volunteer potato plants respectively in 2008. The clay soil plots had between 5.9% and 7.1% volunteer potato plant within the vegetation. On the other hand, on sand soil only between 0.7% and 2.2% of the vegetation was volunteer potato. However, these differences in volunteer potato occurrence in the vegetation were not used in the a priori chances of 98% and 2% that were used in the classification algorithm.

Table 5.1 Occurence of sugar beet and volunteer potato grid cells during the six measurement days in 2008.

Class	Sugar beet occurrence in vegetation %	Volunteer potato occurrence in vegetation %
Date of measurement		
2008-05-28 clay soil	92.9	7.1
2008-05-30 clay soil	93.6	6.4
2008-06-02 clay soil	94.1	5.9
2008-05-28 sand soil	97.8	2.2
2008-05-30 sand soil	99.1	0.9
2008-06-02 sand soil	99.3	0.7
Average	96.1	3.9

Feature quality

Based on the ground-truth images, the amount of variance that the features explained between the classes was investigated. At maximum six variables were selected with this procedure to explain the variance between the two classes. Table 5.2 gives the features that were selected with the discriminant analysis. The maximum variance was 1 and decreased as variables were entered in the discriminant analysis.

Table 5.2 Features that explained the highest amount of variance during the experiments on the 7 measurement days in 2007 and 2008. Features are ordered from 1 to 6, from high to low amount of variance explained between the sugar beet and volunteer potato class. The variance given is the amount of unexplained variance after inclusion of that specific feature.

Feature	1	2	3	4	5	6
Date of measurement						
2007-09-13	sat	NDVI	hue	RB	-	-
sand soil	0.474	0.354	0.346	0.344		
2008-05-28	NDVI	sat	EG	-	-	-
clay soil	0.560	0.393	0.386			
2008-05-30	sat	hue	nir	-	-	-
clay soil	0.653	0.560	0.549			
2008-06-02	sat	hue	NDVI	EG	red	RB
clay soil	0.603	0.562	0.547	0.542	0.516	0.513
2008-05-28	sat	nir	EG	RB	NDVI	hue
sand soil	0.640	0.625	0.619	0.617	0.607	0.602
2008-05-30	blue	hue	nir	sat	-	-
sand soil	0.808	0.753	0.710	0.692		
2008-06-02	nir	hue	EG	RB	NDVI	-
sand soil	0.940	0.921	0.916	0.895	0.886	

Except for the sand soil at 2008-06-02, saturation was in all experiments used as a discriminative feature. Furthermore, hue and NDVI were selected frequently as discriminative parameters. In 2007, the lowest amount of variance remained unexplained. In 2008, the experiments on the clay soil had a smaller amount of unexplained variance compared to the experiments at the sand soil. The features mean red, mean green, and mean intensity were in none of the experiments selected as discriminative feature. The information in these features was either correlated to the other color features that were already selected, or was not of discriminative power in these fields between the two classes.

Classification accuracy

In 2007, the algorithm performed well on the detection of VP and SB (Table 5.3). Over 95% of VP was classified correctly, but this was accompanied with 8.0% misclassified SB. This was a too high percentage as only 5.0% misclassification was allowed in the program of requirements. Then, in 2008, on the clay soil plot 82, 91, and 78% of the VP were classified correctly. This was accompanied with a misclassification of SB of 4, 7, and 20%. These numbers show that the performance decreased when the plants grew larger. Apparently, the color features of the VP and SB are approaching each other with increasing growth stage. In the sand soil plot, 20, 4, and 0% were correctly classified as VP with 25, 38, and 30% of SB misclassification. These values are almost opposite of the results obtained on the clay soil plot.

Table 5.3 Classification performance of the real-time algorithm for the seven experiments in 2007 and 2008. The confusion matrix and the classification accuracy are given as percentages where True negative (TN), False negative (FN), False positive (FP), True positive (TP), Volunteer potato (VP) and Sugar beet (SB) are used.

Date of measurement	Ground truth	# of plants	Result VP	Result SB	Classification accuracy
Example	VP	--	TN	FP	--
	SB	--	FN	TP	
2007-09-13	VP	29	96.6	3.4	92.5
sand soil	SB	263	8.0	92.0	
2008-05-28	VP	84	82.1	17.9	94.6
clay soil	SB	729	4.0	96.0	
2008-05-30	VP	98	90.8	9.2	92.4
clay soil	SB	846	7.4	92.6	
2008-06-02	VP	110	78.2	21.8	79.9
clay soil	SB	932	19.8	80.2	
2008-05-28	VP	61	19.7	80.3	71.2
sand soil	SB	889	25.3	74.7	
2008-05-30	VP	25	4.0	96.0	60.7
sand soil	SB	969	37.9	62.1	
2008-06-02	VP	0	0.0	0.0	70.1
sand soil	SB	230	29.9	70.1	

The large amount of unexplained variance in the features, as shown in Table 5.2, supports the poor performance of the Bayes classifier. As a result of conventional weed control practices with non selective herbicides, no clear differences existed in the color features between the classes in this field. The weed control practices mid of May 2008 resulted in deteriorated leaves on volunteer potato plants. The impact of weed control practices is confirmed by Table 5.1 listing the number of counted VP in the ground truth data set. On sand soil the number of plants was low and decreased as a result of the conventional full field weed control treatment. However, the plants were not completely removed as a result of the conventional weed control treatment (Paauw & Molendijk, 2000). The quality of classification may be further improved by adapting $P(C_i)$ from Equation 5.7 according to the actual occurrence of the vegetation as shown in Table 5.1.

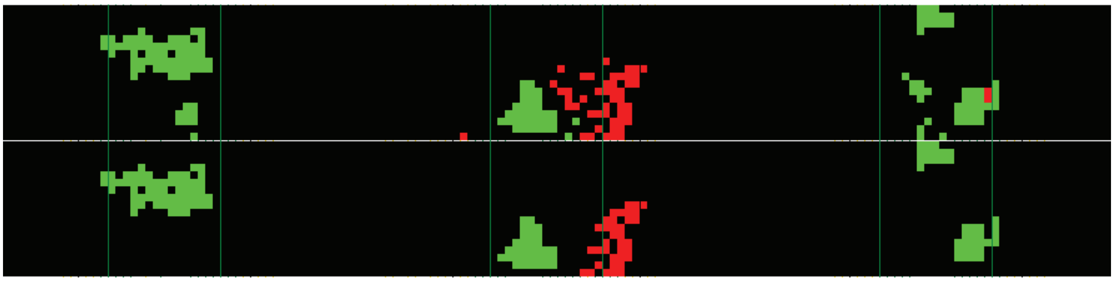

Figure 5.12 Result of classification (upper image) and after applying the small plants filter of Equation 5.8 (bottom image).

Expected classification quality

In 2007, Mahalanobis and Fréchet distance were not yet implemented, so these values could not be determined. In 2008, both distance measures showed larger values at the clay soil compared to the sand soil experimental field. This is in accordance with the classification accuracies (CA) as shown in Table 5.4. It is expected that when two multivariate distributions are closer to each other that this is accompanied with a higher risk of misclassification.

Table 5.4 The mean Mahalanobis and mean Fréchet distances and corresponding standard deviation (s.d.) given for the six experiments in 2008. The classification accuracy and number of images are presented as well to compare the distance measures with the Bayes classifier results.

Date of measurement	Classification accuracy	# images	Mahalanobis mean (s.d.)	Fréchet mean (s.d.)
2007-09-13 sand soil	92.5	134	--	--
2008-05-28 clay soil	94.6	439	6.68 (1.55)	6.78 (1.25)
2008-05-30 clay soil	92.4	467	9.77 (2.49)	6.40 (1.15)
2008-06-02 clay soil	79.9	479	11.67 (6.15)	5.77 (1.14)
2008-05-28 sand soil	71.2	564	5.66 (1.24)	4.67 (0.86)
2008-05-30 sand soil	60.7	475	3.79 (1.31)	5.16 (1.68)
2008-06-02 sand soil	70.1	252	2.83 (0.65)	3.48 (0.58)

When comparing Mahalanobis with the Fréchet distance as quality parameter, Fréchet distance outperforms for the following reasons: 1) The Fréchet distance decreases when the CA decreases on clay soil, whereas the Mahalanobis distance increases with decreasing CA on clay soil, 2) The Fréchet distance has a smaller standard deviation (s.d.) which is preferred for a system where a threshold will be based on the quality of classification, so that economic risks of misclassification can be minimized. In general, both distance measures were capable of identifying the poor classification performance on the sand soil. This was emphasized as an Anova ($P<0.05$) showed that the values of the distances were significantly different for the clay and sand soils.

Real-time performance

The classification algorithm was implemented in a real-time operating system. This required that an accurate analysis of the calculation times was made. In the processor, time is consumed by the algorithm for fixed and variable elements. An overview of the time needed for processing of an image that consisted of approximately 75% green vegetation is given in Table 5.5. The time for preprocessing consisted of illumination correction and Bayer decoding of raw8 images into color images. The overhead was used for network communication and communication with the FPGA. From the variable time elements, the calculations for the feature values of the grid cells took most of the time. Specifically, the calculation of hue, saturation and intensity from the red, green and blue values consumed the largest amount of time, as this was done on a per pixel basis within each grid cell. In general, the travel speed will be limited by the amount of green vegetation within an image. When smaller growth stages are processed, the calculation time per image decreases, and accordingly the travel speed may be increased. An amount of 75% vegetation equals a sugar beet crop row width of 37.5cm, which is about the maximum growth stage in which the detection and control system is required to work. The time that is required for variable elements increased linearly with the number of vegetation grid cells that were present within the image.

Table 5.5 Overview of the real-time algorithm elements and the calculation time that was required. Elements are separated in fixed and variable elements per image.

Time element	Time [ms]
Fixed	
Preprocessing	30
Overhead	5
Subtotal	35
Variable	
Excessive green	15
Vegetation grid cells	25
Feature vector calculation	95
Bayes classification	25
Subtotal	160
Total	195

5.5 General discussion

In this research the crop row detection was not designed to steer an implement or vehicle between the rows. But to train an adaptive classifier. Therefore, not only the crop row position but also the crop growth stage measured as crop row width was measured. The inclusion of measuring growth stage and crop row width is a valuable addition to existing row recognition algorithms from e.g. Tillett and Hague (2006) and Bakker *et al.* (2008) because the growth stage can also be used to determine the aggressiveness or working width of implements. Furthermore, the row position information is valuable information for more precise positioning of an actuator above the weed potato plants in future volunteer potato control applications.

The vegetation was separated from the background soil with a threshold on the excessive green value defined by Woebbecke *et al.* (1995). This gave satisfactory results, however other researchers have shown that improvements can be made by using improved vegetation indices such as excessive green minus excessive red (Meyer & NetoCamargo, 2008). In addition, Philipp and Roth (2002) proposed online discriminant analysis to improve vegetation-soil separation. One of the cameras in this research also measured near-infrared reflection. This further improved the discriminative feature set, as was also indicated by Gerhards (2003). In future developments online removal and addition of features is required as well, as proposed in Agrawal and Bala (2008). This will further improve the real-time performance and classification performance, as unnecessary data is kept out of calculations.

Adaptive classification algorithms of weeds and crops have been applied in earlier research. For example Tian and Slaughter (1998) applied an algorithm that adapted to the environmental conditions. But this algorithm was mainly focused at eliminating natural light fluctuations and shades, like in the research of Marchant and Onyango (2001) who proposed an algorithm for shadow invariant classification. Our previous research on volunteer potato detection was in uncontrolled light conditions as well, but shading and colour constancy were problems as well (Nieuwenhuizen *et al.*, 2007a; Nieuwenhuizen *et al.*, 2007b). In this research the image recording conditions were controlled with five lamps. Therefore, the adaptive aspects of the adaptive Bayes classification algorithm were to handle the growth stage and color changes of the sugar beet crop and volunteer potato plants. Astrand and Baerveldt (2002) demonstrated that, with controlled light conditions, sugar beets and weeds can be separated with machine vision. Their algorithm used the planting distance within the crop row as a priori information to improve the classification accuracy of the sugar beet plants. Their recommendation to do further experiments on different fields has been adopted in this research, as measurements were done in two seasons and on three fields in several growth stages. Furthermore, the classification on square centimeter grid cell precision reduced problems of other previous researchers with occluding or overlapping plants in larger growth stages.

Quality feedback parameters have -to the best of our knowledge- not yet been reported within machine vision based weed detection systems. In most of the research experiments the quality of a classifier was evaluated afterwards against ground truth images of only a small dataset or subset of the data. Most times, the creation of ground truth images is a compromise between time and required data for evaluation purposes. In this research, a quality parameter was introduced that produces real-time information on the expected classification accuracy, without knowing the actual ground truth. This is a first step towards reliable machine vision based systems in natural environments. Feedback has to be further extended to the other steps in the algorithm, e.g. correct working of the illumination, vegetation detection, crop row detection, classifier training, and actual classification performance. This will further improve the reliability of unsupervised classification algorithms.

Real-time algorithms require deterministic algorithms to ensure that calculations are performed within time limits. Until now, the algorithm was dependent on the amount of vegetation that was in the images. Therefore, some redundant or spare computation time has to be available to guarantee the completion of the classification before new images are recorded. Probably the user could be given an indicator that higher travel speed is tolerated or lower is required based on the amount of green vegetation in prior images. However, constant travel velocity is only an issue on tractor based solutions where the driver has fixed the velocity. One could also consider an autonomous based application like Evert *et al.* (2008) propose with their “Ruud” robot for real-time detection of weeds in grassland. In that case, the algorithm first does a rough classification, and in case of a positive result, speed is lowered or the robot is halted to further increase the spatial accuracy of classification. Processor time can be saved by reduction of the number of features. The mean red, green, and intensity were shown not to be discriminative between VP and SB. Thus, when using less features and in smaller growth stages the travel speed can be increased. In summary, the main challenges for improvements of the algorithm are the inclusion of feedback mechanisms on quality of classification and automatic feature selection techniques to improve the real-time performance of the adaptive Bayes classification.

Further experimental evaluation of the detection system requires that an actuator is connected to the system as well. Then, field trials with an assessment of the biological efficacy can be done. These are needed to fully evaluate the potential in reduction of labor and chemical inputs presented with this study.

5.6 Conclusions

In this research the objective of implementing an unsupervised adaptive algorithm for square centimeter precision volunteer potato detection was successfully achieved and demonstrated in three fields.

The crop row position and crop row width were determined and a Kalman filter improved tracking of the rows. The filter was resistant to erroneous measurements as a result of weed potato plants. This resulted in good quality training data for the Bayes classifier. However, the requirement of classification performance of minimum of 95% VP and maximum 5.0% SB was not achieved in all fields under all circumstances. In the first field 96.6 and 8.0%, in the second field 90.8 and 7.4%, and in the third field 19.7 and 25.3% was achieved. The main reason for the decreased performance in the third field was the deteriorated volunteer potato plants that had been sprayed with conventional herbicides. Fortunately, the Fréchet distance measure, that was used as quality indicator of the classification, predicted with a value of 3.48 $\pm$ 0.58 that the classification would be poor. Using such a quality indicator, the application of glyphosate -with an actuator- can be halted in such a field, to minimize crop damage and economic losses.

The real-time performance was not yet within the requirements of a travel speed of 1.5 m s^{-1}. Specifically, one image with a length of 20 cm was processed within 195 ms maximum.

5.7 Acknowledgement

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Chapter 6

Influence of glyphosate on the tuber yield and photosynthesis activity of volunteer potato (*Solanum tuberosum*) at three growth stages

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6.1 Summary

The objective of this research was to investigate the dose-response relationship between individual volunteer potato plants and glyphosate. This will benefit precision agriculture as herbicides are targeted weed plant specifically. Plants were sprayed on a spray track with six concentrations. The photosynthesis activity and tuber weight were then measured and fitted with log dose-response models for three growth stages. Differences in responses were found for photosynthesis activity and tuber weight, and between growth stages. More glyphosate was needed to inhibit photosynthesis activity in the shoots than was needed to inhibit tuber formation. To reduce shoot growth by 90% at 14 days after treatment, 843, 1121, and 1050 μg a.e. plant^{-1} had to be applied on plants with a height of 6.1, 7.9, and 12.0 cm, respectively. The best size for volunteer potato control was on plants of 6.1 cm. These required 390 μg a.e. plant^{-1} to inhibit tuber production and ED_{90} was 843 μg a.e. plant^{-1} for the shoots photosynthesis activity. Growth stage specific dose response relations are required information for precision application purposes and extensions to other weeds can be made with our method. Updated knowledge of the dose-response relation provides praxis ways of reducing their herbicide use for volunteer potato control.

Keywords: volunteer potato, dose-response, deposition, imaging, glyphosate

6.2 Introduction

Volunteer potato is a serious weed in many potato growing regions where winter temperatures are often not cold enough to kill tubers left in the ground after harvest. Plants sprouting from overwintered tubers are vigorous, fast growing, and particularly difficult to control in sugar beet and cereals. This is mainly due to the lack of effective herbicides to control volunteer potato plants, including the tubers in the soil (Boydston, 2001). In addition to competing with crops for growth resources, volunteer potatoes can cause problems during crop harvest due to the weed's high moisture content . However, the main reason for removing volunteer potato is disease control. Volunteer potatoes harbor diseases, especially *Phytophthora infestans*, insects, and nematode pests of potato, all of which negate the benefits of crop rotation (Dewar *et al.*, 2000; Boydston & Williams, 2005). Removal is stressed by Dutch legislation, which mandates that volunteer potatoes be eliminated from fields before July 1. Applying partially effective herbicides, rotating to competitive crops, cultivation, and hand weeding are common methods to control volunteer potato, However, these methods are not effective in combating potato haulm and tuber; application of glyphosate is the most effective way to control volunteer potatoes with tubers during the growing season.

Because manual plant specific application of glyphosate is labor intensive and expensive, automatic detection techniques with machine vision have been developed (Nieuwenhuizen *et al.*, 2007). In addition to these detection techniques, plant specific glyphosate application techniques, such as microsprayers, have also been designed (Nieuwenhuizen *et al.*, 2008). These microsprayers reduce the risk of crop injury during plant specific application of herbicides. These new techniques give farmers the perspective of easier control practices that reduce labor, are less dependent on the growth stage of weeds and the crops, and reduce the required amount of herbicides as compared to full field spraying (Graglia, 2004; Sogaard & Lund, 2007). However, for plant specific application of herbicides, we need to know the plant specific dose response.

In the late 1970s, Lutman and Richardson (1978) investigated the activity of glyphosate on volunteer potato plants. Their doses were 0.5, 1.0 and 2.0 kg acid equivalent (a.e.) ha^{-1}. They reported that for the lower dose of 0.5 kg a.e. ha^{-1}, the plants did not completely stop growing or halt tuber production. The highest dose of 2.0 kg a.e. ha^{-1} resulted in few tubers being present at harvest 50 days after treatment (DAT) and in stopping shoot growth. Smid & Hiller (1981) reported doses between 0.28 and 1.12 kg a.e. ha^{-1} for haulm removal and tuber inhibition, and higher doses did not improve reductions in shoot and root dry weight. In both studies the actual plant sizes and growth stages used were not clearly described. Furthermore, the reported doses may no longer be valid due to changes in commercial glyphosate formulations and their surfactants as described by Sharma and Singh (2007). Also, changes in vigorousness of the commercial potato varieties used nowadays can influence the dose response relation (Diepen, 2007).

To determine the optimal plant growth stage (GS) for the application of glyphosate, it is important to know when the volunteer potato plants are most sensitive to glyphosate. However, this stage was not described by Lutman and Richardson (1978) or Smid & Hiller (1981), and to the best of our knowledge, no other studies have been reported that focus on determining the GS of volunteer potato most sensitive to glyphosate in terms of mortality and tuber yield. Therefore, the objective of this research was to investigate the dose-response relationship between glyphosate and growth of the individual volunteer potato plant. The research questions were (1) what is the dose-response of tuber yield and photosynthesis activity of volunteer potato to glyphosate, (2) what is the amount of acid equivalent at which no new tubers are formed, and (3) what is the best GS for volunteer potato control, i.e., which stage needs the smallest amount of acid equivalent to inhibit photosynthesis fully and to prevent any tuber yield.

6.3 Materials and methods

In a laboratory experiment a range of doses of glyphosate were applied to potted potato plants of three GS. After treatment, the temporal evolution of the photosynthesis activity of the plants and the weight of the newly developed tubers were measured as effect parameters to determine best control practice for volunteer potatoes. For future plant specific application techniques, the ground covered area of the plants was measured using images and the spray deposition on leaves was measured using a fluorescent tracer.

Potato plants and experimental design

Potato tubers from 28 to 35 mm long, cultivar *Asterix*, were obtained from a commercial farm. The *Asterix* cultivar was chosen because it has a quick and strong shoot growth (Diepen, 2007), and it poses a large problem as volunteer potato. Three groups of 40 potato plants each were grown in 5.0 L plastic pots with a sandy soil. The tubers were planted on April 13, 2006. The GS of the volunteer potato plants were characterized based on height and ground covered surface area (Table 6.1). The height was measured with a ruler, and the ground covered surface area was measured with an imaging setup that was calibrated using software (Vision Assistant 8.0, National Instruments, Austin, TX, USA). Thus, the green pixels in the image could be transformed to square centimeter ground covered surface area. On May 8, 2006, 40 plants in GS I and 40 plants in GS II were treated; and then on May 23, the remaining 40 plants in GS III were treated, the growth stage characteristics are given in Table 6.1. The plants were grown outside and watered regularly. The weather conditions during the 28 days after treating GS I and GS II plants on May 8 were an average temperature of 14.7 °C and relative humidity of 69%. During the 28 DAT of GS III plants on May 23, the average temperature was 15.0 °C with a relative humidity of 70% (Antonysen, 2008).

The experimental design was a randomized design split plot design, with two factors: growth stage (GS) as the main factor and glyphosate dose as the second factor. There were five replicates of each dose. The remaining five plants were separated for the spray deposition measurements using a fluorescent tracer.

Spraying

A commercial formulation of glyphosate (Roundup Max®, 450 g L^{-1}, Monsanto, Enkhuizen, The Netherlands) was applied to the volunteer plants with a compressed air-driven hydraulic track sprayer equipped with three XR11004 (TeeJet, Spraying Systems Co., Wheaton, IL, USA) flat fan nozzles that delivered 300 L ha^{-1} at $3.0 \cdot 10^5$ Pa. The nozzle spacing on the spray boom was 50 cm and the boom height above the crop canopy was 50 cm. The tap water for the spray solution had a hardness of 31.4 mg L^{-1} calcium carbonate and an electrical conductivity of 200 μSiemens cm^{-1}, classified as soft water. The applied doses were 0.14, 0.68, 1.35, 2.70, 6.75 and 13.5 kg a.e. ha^{-1}, respectively. The indoor climatic conditions in the spraying cabin were 20 °C with a relative humidity of 70%. After spraying, the deposit was allowed to dry before the plants were placed outside.

Effect parameters: photosynthesis activity and tuber weight

The photosynthesis activity and the tuber weight were chosen as effect parameters of the treatments. Although glyphosate is not known to interfere directly with the photosynthesis system of plants, its secondary effects on the photosynthesis system of plants can be measured (Christensen *et al.*, 2003; Abbaspoor & Streibig, 2005). Chlorophyll fluorescence and photosynthesis activity of the dark adapted plants were measured as described by Franzaring *et al.* (2001), using a portable plant photosynthesis meter (Model PPM, EARS, Delft, The Netherlands). Measurements took place 1, 3, 5, 7, 9, 14, 21, and 28 DAT. The photosynthesis measurement device gave photosynthesis activity values in arbitrary units, ranging from 20, indicating dead material with no photosynthesis activity, to 80 and higher, indicating healthy growing plant material. In mid–August, the tubers of the plants were harvested and weighed. Prior to weighing, the tubers were cleaned with water and soil was removed.

Deposition

The deposition of the spray droplets on the potato plants was measured using a tracer (Brillant Sulfoflavine, BSF, C.I. 56205 1F 561, Chroma-Gesellschaft, Münster, Germany). From each GS, as listed in Table 6.1, five plants were sprayed with the same equipment and settings as those used in the glyphosate dose response experiment described above. The spraying solution consisted of tap water mixed with 0.203 g L^{-1} BSF, and 1 mL L^{-1} of the surfactant (Agral LN®, 250 g L^{-1}, Syngenta, Roosendaal, The Netherlands) was added as it is commonly used in spray deposition experiments (Taylor & Shaw, 1983; Phillips & Miller, 1999; Zande *et al.*, 2005).

Table 6.1. Growth stage characteristics of the potato plants in the experiment. The average of the plants for each growth stage (GS) are given with their standard deviations between parentheses.

	GS I	GS II	GS III
Height (cm)	6.1 (1.39)	7.9 (1.01)	12.0 (1.578)
Area average (cm^2)	53.3 (19.66)	89.4 (18.48)	111.2 (14.38)

After spraying and drying, the individual leaves were cut and washed with 10 mL water over 15 min. Then, the fluorescence of the resulting extract was measured with a fluorimeter (LS45, PerkinElmer Ltd, Beaconsfield, England). To verify recovery of the deposits from the potato leaves, 10 µL liquid containing 0.203 g L^{-1} BSF was micro-applied on ten leaves and in three empty pots to provide a reference for the actual plant deposits based on the fluorescence response using the same method as in Stallinga *et al.* (2006). The result of this procedure was the deposition in µL per plant. These plant depositions were divided by their respective ground covered surface areas to calculate the specific deposition in µL cm^{-2} for each GS.

Plant specific approach

We used equation (6.1) to calculate the plant specific amount of acid equivalent:

$$\frac{\text{acid equivalent}}{\text{plant}}[\mu\text{g}] = \text{area}\,[\text{cm}^2]\cdot\text{specific deposition}\left[\frac{\mu\text{L}}{\text{cm}^2}\right]\cdot\text{concentration}\left[\frac{\mu\text{g}}{\mu\text{L}}\right] \tag{6.1}$$

The ground covered surface area of the plants was determined with machine vision. The specific deposition on the plants corresponded to the deposition on the plants determined with the fluorescence measurements. These two factors multiplied with the concentration of glyphosate in the spray fluid yielded the amount of acid equivalent deposited on the plant, as shown in equation 6.1.

Statistical analysis

Based on the height and the ground covered surface area, the GS were confirmed to be significantly different showed by ANOVAs with a post hoc LSD test at $\alpha = 0.05$.

Data were analysed according to the following procedure. Firstly, plant photosynthesis activity was plotted as a function of the time after treatment to determine the photosynthesis inhibiting effect of glyphosate. Then, the results were evaluated by analysis of variance. Main effects were separated by LSD. The next step was to investigate the photosynthesis activity decrease within the first weeks and specifically for 7 and 14 DAT. This is important because the sooner plant growth diminishes, the less risk the plant has of spreading disease. Finally, photosynthesis activity measurements and tuber weight (as a second effect parameter) were fitted with dose-response models.

The effect parameters were regressed on the glyphosate dose, based on the log-logistic nonlinear regression method described by Seefeldt *et al.* (1995) and in our form shown in equation 6.2:

$$y = \delta + \left(\frac{(\alpha - \delta)}{1 + \left(\frac{K}{100 - K} \right) \exp(\beta(\log(x) - \log(\gamma_K)))} \right) \tag{6.2}$$

where α, β, γ_k and δ represent the upper limit, slope, effective dosage causing K % response (µg a.e. plant^{-1}) and lower limit of the predicted curve, respectively. The average response of the control groups was set as α, and δ was chosen as the lowest possible value for tuber weight, 0 g, and the lowest possible value for photosynthesis activity, i.e. 20. For K, both 50% and 90% reduction in effect parameter (ED_{50} and ED_{90}) were used as values for effective dose determination because it is extremely important to reduce the weed pressure of volunteer potatoes as much as possible in the field. The log-logistic dose-response curves of the three GS were compared to check for differences or similarities between the responses. Two models were compared. Firstly, a full model with β and γ_k was determined for each GS by the regression procedure. Secondly, a reduced model was fitted with a common β and γ_K for the three GS. A lack-of-fit F-test (equation 6.3) was performed to see if the full model could be replaced with the reduced model (Schabenberger & Pierce, 2002):

$$F = \frac{(SS_{e;reduced} - SS_{e;\,full}) / (DF_{e;reduced} - DF_{e;\,full})}{MS_{e;\,full}} \tag{6.3}$$

where SS_e is error sum of squares, DF_e is degrees of freedom, and MS_e is mean squares. It was hypothesized that the reduced model would describe the observations from the three GS and no significant differences in response between GS would be found. On the other hand, when the full model was needed to describe the three GS, the parameter estimates for β and γ_k should have shown where the differences were present in response to the glyphosate doses. All statistical tests were done at a significance level of α = 0.05.

6.4 Results

Photosynthesis activity after treatment

Photosynthesis activity of the treated plants changed over time, and from 14 DAT onwards, some treated plants showed minimal photosynthesis activity. The number of plants that showed photosynthesis activity from 14 DAT onwards is shown in Table 6.2. GS III was not measured at 28 DAT.

Figure 6.1 shows the time series of averaged photosynthesis activity for each GS of the plants for each dose that was applied to the plants. The photosynthesis activity of the plants changed over time, except for the control and 0.14 kg a.e. ha^{-1} application at GS III (Figure 6.1). During the first 7 days, photosynthesis activity decreased as doses increased for plants in all three GS. Then, at 9 DAT, plants at GS I and II recovered from glyphosate application at doses 2.70 kg a.e. ha^{-1} and 6.75 kg a.e. ha^{-1}, respectively. GS III plants recovered from the glyphosate application at 14 DAT for doses below 2.70 kg a.e. ha^{-1}. In general, the 6.75 kg a.e. ha^{-1} and 13.5 kg a.e. ha^{-1} application rates inhibited photosynthesis activity for all three GS at T $\geq$ 14 DAT. GS III showed no reaction to the 0.14 kg a.e. ha^{-1} application.

Table 6.2. Number of plants that showed photosynthesis activity values $\geq$ 20 at 14, 21, and 28 DAT. For growth stage III, no photosynthesis measurements were done at 28 DAT.

	Growth stage I			Growth stage II			Growth stage III		
DAT	14	21	28	14	21	28	14	21	28
Glyphosate (kg a.e. ha^{-1})									
0	5	5	5	5	5	5	5	5	x
0.14	5	5	5	5	5	5	5	5	x
0.68	5	5	5	5	5	5	5	5	x
1.35	4	3	3	4	4	2	5	1	x
2.70	0	0	0	1	1	1	0	0	x
6.75	0	0	0	0	0	0	0	0	x
13.5	0	0	0	0	0	0	0	0	x

The response means at 7 DAT and at 14 DAT were significantly different ($P < 0.001$). Therefore, two different log-logistic dose response models had to be fitted for the photosynthesis activity 7 and 14 DAT.

Deposition results and ground covered surface areas

Table 6.3 shows the ground covered surface area, plant deposition, calculated specific deposition per cm^2, and recovery. Tested with ANOVA, the calculated specific deposition per cm^2 for the three GS were not significantly different ($P = 0.394$). Therefore, in the remainder of this work each GS was treated the same because it received the same amount of spray deposit per cm^2 leaf area, and the overall mean specific deposition of 1.81±0.25 μL cm^{-2} was used as the specific deposition factor in Equation 6.1. The recovery percentages represented the amount of spray fluid that was traced back as a percentage of the theoretically 3 μL cm^{-2} that was sprayed.

Table 6.3. Ground covered surface area, deposition per plant, specific deposition, and recovery. The average of the five plants for each growth stage are given with their standard deviations between parentheses.

Growth stage	I	II	III
Area (cm^2)	79 (16.8)	98 (7.19)	148 (18.4)
Plant deposition (μL)	146 (20.1)	178 (9.9)	250 (34.0)
Specific deposition (μL cm^{-2})	1.92 (0.408)	1.82 (0.117)	1.69 (0.087)
Recovery (%)	64	61	56

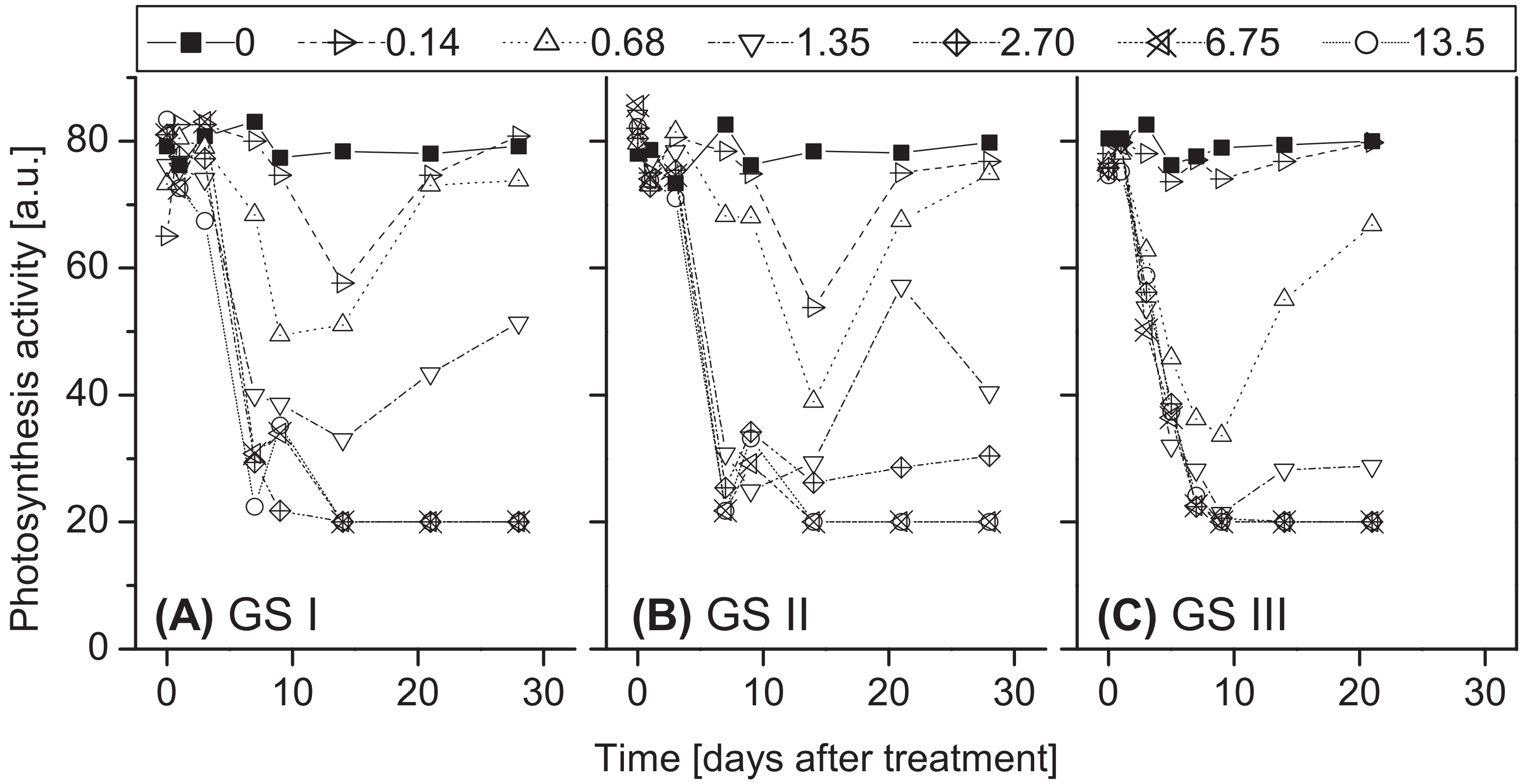

Figure 6.1. Time series of photosynthesis activity of (A) GS I, (B) GS II, and (C) GS III plants after spraying. The values are the average photosynthesis activity of five plants (measured with a portable plant photosynthesis meter – PPM, EARS, 2006) as a response to the application of six doses of glyphosate, in kg a.e. ha^{-1}.

Table 6.4 Summary of dose-response regressions of photosynthesis activity and tuber weight parameters. Asymptotic 95% confidence intervals are given in parentheses. Significantly (α=0.05) different estimated parameters are marked with alphabetic characters.

Experiment	α	δ	β	ED_{50} (µg a.e. plant^{-1})	ED_{90} (µg a.e. plant^{-1})	Sum of squares reduction F-test $F_{4,84}$	P-value
Photosynthesis activity							
7 DAT						4.72	<0.005
Growth stage I	83	20	1.92 (1.08-2.76)^{a}	311 (251-372)^{g}	978 (493-1461)^{l}		
Growth stage II	83	20	7.62 (3.51-11.72)^{b}	498 (458-538)^{h}	665 (553-776)^{l}		
Growth stage III	78	20	2.20 (0.95-3.44)^{a}	326 (216-435)^{g}	884 (470-1298)^{l}		
Photosynthesis activity							
14 DAT						20.48	<0.005
Growth stage I	78	20	1.18 (0.86-1.50)^{c}	131 (98-164)^{i}	843 (448-1238)^{m}		
Growth stage II	78	20	1.01 (0.71-1.31)^{c}	127 (85-169)^{i}	1121 (468-1774)^{m}		
Growth stage III	79	20	3.19 (1.92-4.46)^{d}	527 (463-591)^{j}	1050 (748-1351)^{m}		
Tuber weight						5.25	<0.005
Growth stage I	44	0	2.50 (1.72-3.27)^{ef}	162 (133-190)^{k}	390 (285-494)^{n}		
Growth stage II	52	0	2.77 (1.96-3.57)^{e}	183 (147-219)^{k}	404 (293-515)^{n}		
Growth stage III	50	0	1.43 (1.09-1.77)^{f}	189 (146-231)^{k}	879 (531-1227)^{o}		

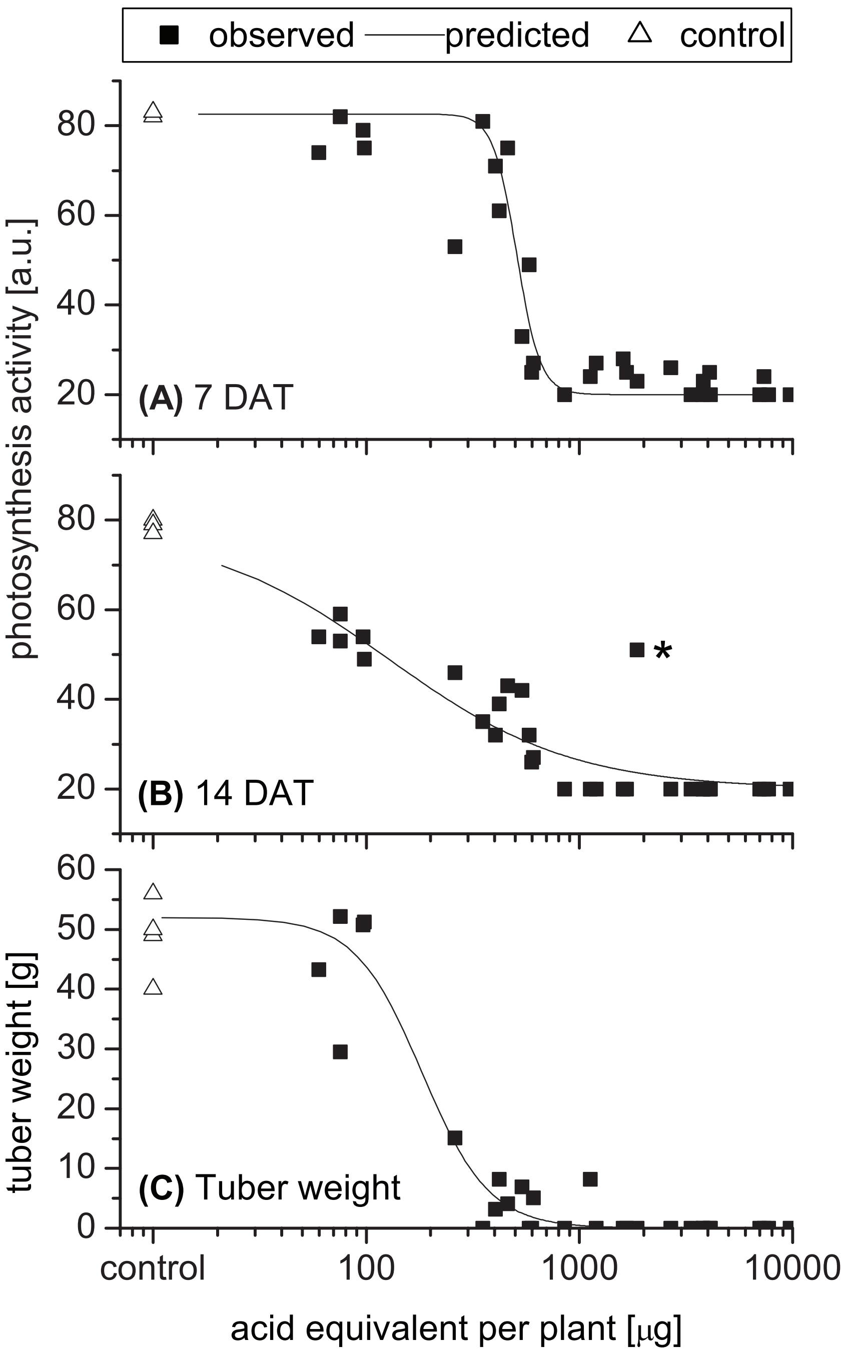

Figure 6.2. Photosynthesis activity at (A) 7 DAT, (B) 14 DAT and (C) tuber weight as a function of acid equivalent per plant. (C) Log logistic predicted model, observed data, and control values for growth stage II. Observation marked with * was not used for the prediction and parameter estimation as it was outside the range of the confidence interval of the full model including this observation.

Dose response effects

For the parameters studied (photosynthesis activity at 7 DAT and at 14 DAT and tuber weight), the null hypotheses of no differences between the three models and responses were rejected ($P < 0.005$). Thus, three models were fitted for each GS, and the parameters estimated are given in Table 6.4. Dose response curves for GS II are presented in Figure 6.2.

Photosynthesis dose response at 7 DAT

The three fitted models could not be considered similar ($F_{4,84} = 4.72$, $P < 0.005$). The ED_{50}-value for GS II is estimated at 498 μg a.e. per plant and was significantly higher as compared to GS I and III. The ED_{90} value for photosynthesis reduction was 978 μg a.e. on GS I, but this was not significantly different from ED_{90} at GS II and III. However, a significant steeper dose response curve was modeled at GS II.

Photosynthesis dose response at 14 DAT

The three fitted models could not be considered as similar ($F_{4,84} = 20.48$, $P < 0.005$). At 14 DAT, the doses needed to achieve the same result were higher than those at 7 DAT. The ED50-value for GS III was significantly higher than that for either the GS I or GS II plants (see Table 6.4). For the ED90-values GS II plants needed the highest amount of 1121 μg a.e. to inhibit photosynthesis activity, but this was not significantly different from GS I and II.

Tuber weight dose response

The tuber weight was regressed on the total amount a.e. per plants as well. The three fitted models could not be considered similar ($F_{4,84} = 5.25$, $P < 0.005$). As ED_{50} values did not differ significantly among GS, the slope (β) was mainly responsible for the need of three models (see Table 6.4). Actually, the β of GS III was low, which indicated a lower sensitivity to increasing total amount of a.e. as compared to GS I and II, with regard to tuber production. The ED_{90}-value of GS III volunteer potato plants was significantly higher at 879 μg a.e. plant^{-1} than that of either GS I or GS II.

6.5 Discussion

Temporal evolution of photosynthesis activity

It was not known beforehand whether the three GS would respond with the same speed of action of glyphosate. The time series of photosynthesis activity measurements showed that all three GS had reduced photosynthesis activity after spraying. The higher concentrations of 6.75 kg a.e. ha^{-1} and 13.5 kg a.e. ha^{-1} gave the fastest reduction in photosynthesis activity as their photosynthesis activity was at 20 – meaning no photosynthesis activity – 7 DAT. The speed of action of glyphosate is important to reduce weed competition with the crop. Plants sprayed with lower concentrations showed an increase in photosynthesis activity from 14 DAT onwards. The photosynthesis activity curves indicate that photosynthesis was inhibited in most of the plants within 14 DAT. With some exceptions, the decline of the photosynthesis activity before 10 DAT was almost similar for all doses and GS. The response of the plant to the herbicide was significantly different between GS III and the other two GS for the doses 0.14 kg a.e. ha $^{-1}$ and the 0.68 kg a.e. ha $^{-1}$, respectively. GS III shows no response to 0.14 kg a.e. ha $^{-1}$ glyphosate, and a stronger response to 0.68 kg a.e. ha $^{-1}$ glyphosate. One might expect that if larger plants have a high growth rate, then glyphosate translocation would be faster and photosynthesis activity would be inhibited in a shorter time.

Farmers measure the photosynthesis activity of weeds after herbicide application in the field to determine the spraying efficacy (Kempenaar & Lotz, 2004). Our results show that it is advisable to measure photosynthesis activity of volunteer potato later than 10 DAT because the results indicate that the decreasing photosynthesis activity in the first 10 DAT is not a reliable indicator for the efficacy of the glyphosate application. In a practical situation, however, farmers should measure the photosynthesis activity of their volunteer potato plants at 14 DAT. When photosynthesis is inhibited at 14 DAT, tuber formation will be completely inhibited as well, and this protects the crop rotation from new volunteer potato plants.

Our results indicate that higher amounts of glyphosate are needed to stop shoot and tuber growth as compared to the photosynthesis and tuber formation inhibiting doses reported by Smid and Hiller (1981) – 1.12 kg a.e. ha $^{-1}$ – and by Lutman and Richardson (1978) – 2.0 kg a.e. ha $^{-1}$. Accordingly, an optimal treatment practice for the *Asterix* cultivar would be to use a 6.75 kg a.e. ha $^{-1}$ concentration to spray on GS I volunteer potato plants, as these plants need the smallest amount of glyphosate to inhibit tuber yield and photosynthesis activity fully. The weather conditions of the two application days were also studied to investigate their influence on the responses because the third GS was sprayed 15 days later than GS I and II. The weather conditions were almost identical during the 28 days after both treatments and weather effect were not further taken into account.

Deposition and ground covered area imaging

The theoretically applied spray volume was 3 μL cm $^{-2}$ ground surface area. However, our measurements (Table 6.3.) show that only an amount between 1.69 and 1.92 μL cm-2 was found on the potato plants. It is known that recovery percentages in deposition vary between 50% and 90% (Cooke *et al.*, 1986; Nordbo & Taylor, 1991; Zande *et al.*, 2003; Stallinga *et al.*, 2006). Our results, 56% to 64% recovery, are within the ranges described in the literature. The reasons for the lower recovery in our research could be run off to the soil beneath the potato plants or effects due to evaporation to the surrounding air. Another factor that influenced the calculation of GS specific deposition on the plants was the imaging technique. Imaging techniques to determine ground covered surface area cannot measure the area of leaves located at inner canopy layers of the plants since leaves are occluded by other leaves (Soille, 2000; Hemming & Rath, 2001). However, inner canopy leaves intercept spray droplets as well and therefore influence the deposition measured on plants. Due to the small number of plants that were used to measure deposition and the variation in ground covered surface area of those plants, the deposition in μL cm^{-2} could not be separated between GS, and the mean deposition factor of 1.81 μL cm^{-2} was used to calculate the plant specific dose that was applied. In our results we have used the real amounts of acid equivalent deposited on the plants. The deposition from the spraying technique should always be considered when extrapolating the results of dose response experiments to practice or to new or future plant specific application techniques.

Perspectives with regard to plant specific application

For future plant specific application, the amount of acid equivalent for individual plants is required. We measured the ground covered surface area of the plants and linked the individual plant growth stage to a total amount of applied acid equivalent using equation 6.1. Both at 7 and 14 DAT the ED_{90} for photosynthesis activity was not significantly different between growth stages. At 14 DAT the ED_{90} for photosynthesis activity was between 843 and 1121 instead of 665 to 978 μg a.e. $plant^{-1}$ at 7 DAT. We recommend applying the higher amounts of acid equivalent found for the 14 DAT photosynthesis response because a decrease in photosynthesis activity is required within the first two weeks after application to prevent spread of diseases in the field such as *Phytophthora infestans*. The ED_{90} for tuber formation is between 390 and 404 μg a.e. $plant^{-1}$ for GS I and II and significantly higher for GS III with an ED_{90} of 879 μg a.e. $plant^{-1}$. The ED_{90}-values were higher to inhibit photosynthesis at 14 DAT as compared to inhibiting tuber sprouting and new tuber growth. When over 1121 μg a.e. $plant^{-1}$ was given for complete photosynthesis inhibition in the potato haulm, no tubers were formed. Actually, the tuber weight is the only parameter to decide if the treatment was successful as no new plants will start growing from the newly formed tubers, and neither will diseases spread from the newly formed foliage. The best effect parameters to measure in future research is the tuber yield and the shoot weight of the volunteer plants, as the objective is to reduce the weed population. As such, not only the haulm but also the tuber part of the weed has to be removed. It is good practice to change the applied amount of acid equivalent with the changing growth stage of the plants in the fields. In fact, our results show that GS I and II plants had significantly smaller ED_{90} as compared to GS III to inhibit tuber formation. The experiments in this research were only in one specific growth season, with one cultivar, and with one type of soil. Therefore, the results may be extrapolated only to a limited extent, but they are valid for a large potato growing area in the Netherlands.

Application on GS I resulted in the smallest amount of acid equivalent of 843 μg per plant, which achieved full control of shoot growth and tuber production. Manual application of glyphosate with a so called “Selector” deposits between 9000 and 18000 μg a.e. $plant^{-1}$ (Mangnus, 2005) in praxis. Our application is an order of magnitude smaller than the application in practice; farmers are known to overdose when they manually apply glyphosate to volunteer plants. Automatic detection and plant specific application of glyphosate would therefore reduce the actual amount of glyphosate used on a field. The glyphosate can be applied by future weed plant specific control systems that not only target droplets on weed plants as shown by Giles *et al*. (2003) and Graglia (2004), but also reduce the risk of crop injury.

6.6 Conclusions

The relationship between individual potato plants and glyphosate has been described for the *Asterix* potato cultivar. Photosynthesis activity after treatment and newly formed tuber weight were successfully used as effect parameters. Measurement of photosynthesis activity at 14 DAT was more successful in predicting the mortality of the plants as compared to 7 DAT. For future plant specific treatments of volunteer potatoes, the following plant specific amounts of acid equivalent were determined using deposition and imaging measurements. To achieve 90% reduction in tuber formation (ED_{90}), 390, 404, and 879 µg a.e. plant^{-1} had to be applied for GS I, II, and III, respectively. However, to reach ED_{90} for photosynthesis inhibition, 14 DAT 843, 1121, and 1050 µg a.e. plant^{-1} had to be applied for GS I, II, and III, respectively. The best GS for volunteer potato control that was derived from our results was GS I, height 6.1±1.39 cm, area 53.3±19.6 cm^2. This smaller GS needed the least amount of 390 µg a.e. plant^{-1} to reduce tuber production by 90 % as compared to the control plants. It also needed the smallest amount of 843 µg a.e. plant^{-1} to reduce the photosynthesis activity of the shoots by 90%. With the information gathered during our research, volunteer potato plant specific spraying techniques can now be designed and tested in our ongoing project on site-specific removal of volunteer potato plants.

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Chapter 7

Biological efficacy of micro-sprayer applied glyphosate on potato (*Solanum tuberosum*) plants

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Submitted to: Weed Research

7.1 Summary

The objective of this research was to investigate the efficacy of micro-sprayer applied glyphosate on potato plants. Therefore 375 greenhouse-grown potato plants were sprayed with five treatments: 1) a flat fan nozzle with water, 2) a flat fan nozzle with a gel, a micro-sprayer with a gel with 3) a low, 4) a medium, and 5) a high density droplet distribution pattern of 676, 1330, and 3022 droplets m^{-2} respectively. The photosynthesis activity, the total leaf dry weight, and the tuber weight were the effect parameters.

The flat fan gel application and micro-sprayer high density droplet distribution pattern showed significantly reduced photosynthesis activity compared to the micro-sprayer low and medium droplet distribution pattern. The total leaf dry weight was significantly lower at 37% for the flat fan gel application compared to the flat fan water application that gave 42% of the weight of the control. The total leaf dry weight was significantly lower for the flat fan gel application and the micro-sprayer high density droplet distribution pattern, with a reduction of 37% and 39% respectively, compared to the low and medium droplet distribution pattern of the microsprayer, with a reduction of 47% and 46% respectively.

The perspectives for using a micro-sprayer or drop on demand system are promising as potato plants were destroyed with glyphosate in gel with the droplet patterns used. A micro-sprayer outperforms flat fan applications as the droplets are targeted, no runoff occurs and a better herbicide efficiency per unit area treated is obtained. The herbicide savings of a micro-sprayer compared to an on-off switching flat fan nozzle ranges from 27% to 95%.

Keywords: dose-response, efficacy, spray, volunteer potato, micro-sprayer, flat fan

7.2 Introduction

Volunteer potato (***Solanum tuberosum***) is a problem in many potato growing regions where natural frost conditions do not kill the tubers left over after the harvest. Plants emerging from these overwintered tubers are vigorous in growth and difficult to control in sugar beet crops as no selective herbicides are available that control haulm and tubers (Boydston, 2001). Volunteer potato plants however, are negating the benefits of the crop rotation as they are the source of ***Phytophthora infestans***, host to nematodes, and a source of unwanted herbivores (Dewar ***et al.***, 2000; Boydston & Williams, 2005). Application of glyphosate on volunteer potato plants is very effective not only for control of the potato haulm, but also for control of the tubers in the soil (Lutman & Richardson, 1978; Masiunas & Weller, 1988). However, undesired drift from application of glyphosate can cause severe crop damage (Roider et al., 2007). Therefore several specific glyphosate application mechanisms have been used in praxis to overcome crop damage due to unwanted glyphosate application to crop plants. Most common are manual or band spray and roller application (Zande & Rops, 1994; Womac ***et al.***, 2004) where only parts of the field are treated with glyphosate. Drawbacks of manual application are the high labor inputs and its related economic consequences for weed control. Drawbacks of band sprayers or glyphosate rollers based on height differences between the weed and crop plant are that they both do not completely control volunteer plants in the field. A manual application of glyphosate is therefore required to suppress the remaining volunteer potato plants. However, in the Netherlands volunteer potato plants have to be controlled as legislation requires the plants be removed before the 1st of July of the growing season (Kienhuis & Berge, 2003) to prevent the spread of ***Phytophthora infestans*** in potatoes.

To overcome the drawbacks of manual application and uncontrolled plants in the field, automated detection and micro-sprayer systems have been designed as described by Sogaard & Lund (2007) and Downey ***et al.*** (2004) for weed seedlings and by Nieuwenhuizen ***et al.*** (2007; 2008a; 2008b) for volunteer potato plants. These systems consist of sensor based detection of the weeds and specific application of a herbicide. For that purpose a micro-sprayer has been developed. Micro-sprayers are systems that deposit targeted droplets on demand onto identified individual weed targets. For these targeted droplet positioning systems to function properly, sophisticated vision systems are used as detection system for the size and place of the weeds. When the size of the weeds is known it is possible to adapt the deposition on the weed plants by changing the number of droplets that are deposited with the micro-sprayer. The weed plant specific application of glyphosate minimizes the risk of unwanted spray deposit onto crop plants as well. However, the viscosity of the spray fluid has to be changed compared to traditional flat fan spraying because of splashing and micro-drift effects (Downey ***et al.***, 2004). When viscosity and surface tension are changed, the efficacy of the spray is unknown and will likely have changed (Ennis & Williamson, 1963; Douglas, 1968).To our best knowledge, no research was done on the efficacy of glyphosate on volunteer potato plants and on different droplet spread patterns when they are applied with micro-sprayers.

Goal, criteria, objectives, questions

The present work was done to establish a micro-sprayer configuration that can be used in a field setting for adequate control of volunteer potato plants. This work was done in a laboratory setting, over a range of growth stages of volunteer plants to determine the conditions that could be used in a field equipment setting. The technical performance in terms of precision, splash, and micro-drift is not discussed in this paper. The objective of this research was to investigate the efficacy of micro-sprayer applied glyphosate on potato plants. The main research question was: What are the perspectives in using a micro-sprayer for volunteer potato control? More specifically, the questions were: 1) What are the effects of applying glyphosate in gel instead of glyphosate in water for the control of volunteer potato plants?; 2) What are the differences in response between flat fan and micro-sprayer applied glyphosate on volunteer potato plants?; 3) What are the effects of different micro-sprayer drop distribution patterns on the volunteer plants?; and 4) What is the reduction in use of herbicides compared to traditional on-off switching nozzles?

7.3 Material and methods

To answer the research questions as stated in the introduction, a dose effect experiment was done in November and December 2007 with greenhouse grown potato plants.

(a) Experimental design and potato plants

Five treatments (Figure 7.1) were done on a range of growth stages of volunteer potato plants as they would emerge in a field situation. The plants had an area between 2 and 650 cm^2. The first treatment was the application of a conventional spray fluid with three flat fan nozzles XR11004 (TeeJet, Spraying Systems Co., Wheaton, IL, USA). The second treatment was application of a gel fluid with a single flat fan nozzle. The third, fourth and fifth treatment were application of the same gel fluid with a micro-sprayer in a low, medium, and high density droplet distribution pattern.

For the experiment, 390 potato plants were grown in 5.0 L plastic pots. Potato tubers of the cultivar ***Asterix*** were obtained from a commercial farm. The ***Asterix*** cultivar was chosen as it was used in earlier experiments (Nieuwenhuizen ***et al.***, 2008a). It is known to have a quick and strong shoot growth (Diepen, 2007) and is a large problem as volunteer potato. Because the experiment took place in autumn, a treatment with gibberellic acid for breaking the dormancy of the tubers was necessary (Lovell & Booth, 1967). Our procedure to break the dormancy of the tubers was to cut the tubers in halve and wet them in a 1.0 ppm gibberellic acid solution for 15 minutes. When the tubers were dry, they were planted in the pots. The plants were grown in a greenhouse with a day and night temperature regime of 15 and 8 °C respectively. Light, relative humidity and day and night lengths were similar to the Dutch climate in April and May when volunteer potato plants are growing in the field.

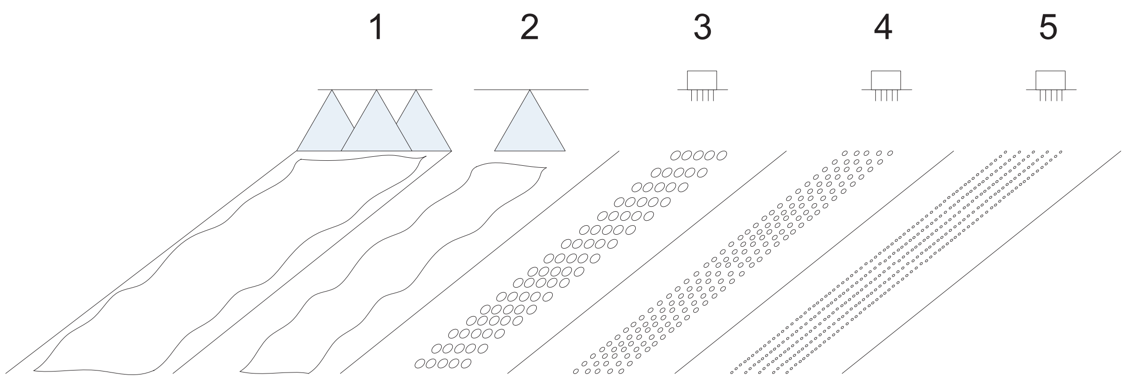

Figure 7.1 Schematic overview of the five treatments were done on the spray track. Treatment 1: a conventional spray fluid sprayed by three flat fan nozzles. Treatment 2: a gel fluid sprayed by one flat fan nozzle. Treatment 3: a low droplet density pattern of gel sprayed by a micro-sprayer. Treatment 4: a medium droplet density pattern of gel sprayed by a micro-sprayer. Treatment 5: a high droplet density pattern of gel sprayed by a micro-sprayer.

(b) Spraying equipment and spraying fluid

In treatment 1 and 2 the spray fluid was applied to the volunteer potato plants with a compressed air-driven hydraulic track sprayer equipped with XR11004 (TeeJet, Spraying Systems Co., Wheaton, IL, USA) flat fan nozzles. The nozzle spacing on the spray boom was 50 cm and the boom height above the crop canopy was about 50 cm. In treatment 1, three nozzles were used. In treatment 2, one nozzle was used, that sprayed gel instead of water. Due to the gel, the spray fluid behaved different compared to water and the gel was evenly distributed under the one nozzle that was used. In treatment 3, 4, and 5 a micro-sprayer was used. The micro-sprayer consisted of a pressurized tank with fluid, five fast acting valves and five needles for droplet formation. The inner diameter of the needles was 0.5 mm and had a cross section area of 0.196 mm^2. The needle spacing on the spray boom was 37.6 mm and the boom height above the crop canopy was about 50 cm identical to the height of the flat fan nozzles. A schematic drawing of the micro-sprayer and the dimensions of a conventional nozzle drawn to similar scale are shown in Figure 7.2. A commercial formulation of glyphosate (Roundup Max®, 450 g L^{-1}, Monsanto, Enkhuizen, The Netherlands) was mixed in different concentrations with either water (treatment 1) or a gel (treatment 2, 3, 4, and 5). Concentrations of Roundup Max® in the tap water solutions were 0.07, 0.25, 0.7, 2.0, and 5.0% ***V/V***. The tap water had a hardness of 31.4 mg L^{-1} calcium carbonate and an electrical conductivity of 200 μSiemens cm^{-1} , classified as soft water. The flow rate of the XR-11004 nozzle was checked at the start of the spraying experiment. At a pressure of $3.0 \cdot 10^5$ Pa and a driving velocity of 6.5 km h^{-1} the spray volume of the nozzles spraying water solution was 300 L ha^{-1} for treatment 1.

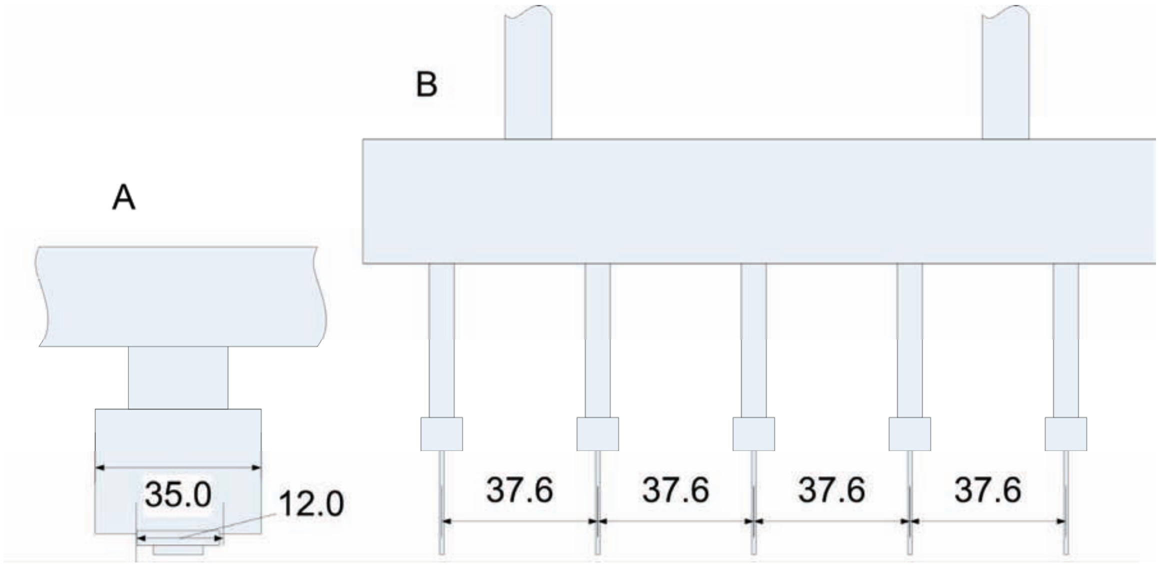

Figure 7.2 Schematic scale presentation shows the dimensions of the micro-sprayer (B) compared to the standard TeeJet XR11004 flat fan nozzle(A). Dimensions have unit [mm].

At a pressure of $6.0 \cdot 10^5$ Pa and a driving velocity of 6.5 km h^{-1} the spray volume of the nozzle spraying the gel was also 300 L ha^{-1} for treatment 2. This resulted in doses of 0.0945, 0.338, 0.945, 2.70, and 6.75 kg a.e. glyphosate ha^{-1}, respectively.

For treatment 3, 4, and 5 the herbicide was mixed in a gel fluid (Agritechnics, Doetinchem, The Netherlands). We applied a low, medium and high droplet density pattern in treatment 3, 4, and 5 respectively. The droplet masses were 14.78, 7.52, and 3.30 mg respectively, measured without glyphosate added in the gel. The distance between the needles creating the droplets in cross-travel direction was 37.6 mm fixed (Figure 7.2). However, in the driving direction the distance between the droplets was 39.4, 20.0, and 8.8 mm between the droplets for the low, medium, and high density droplet pattern. This resulted in droplet densities of 676, 1330, and 3022 droplets m^{-2} for treatment 3, 4, and 5 that were applied at a forward velocity of 1.8 km h^{-1}.

The spray volume in treatment 3, 4, and 5 was 100 L ha^{-1}, which was a factor 3 lower than the application rate for the flat fan nozzles, due to the technical limitations of applying larger droplets with our micro-sprayer. To compensate for the lower application rate, the Roundup Max® concentrations used in the micro-spray treatments 3, 4, and 5 were tripled compared to treatment 1 and 2 with the flat fan nozzles and were 0.21, 0.75, 2.1, 6.0 and 15% ***V/V*** Roundup Max®. The tripled concentrations were chosen such that the same dose per ground covered surface area within the five treatments. This resulted in doses of 0.0945, 0.338, 0.945, 2.70, and 6.75 kg a.e. ha^{-1} as well, identical to the flat fan applications. Instead of water, a gel was used to apply glyphosate on plants. The micro-sprayer was used with gel instead of water, as a water application resulted in unwanted splash to neighboring crop plants and a gel application had reduced to minimal splash. Gel is not a common spray fluid, therefore the viscosity and shear stress properties of the fluid are presented. The gel that was used as application fluid had a higher viscosity with lower shear stress conditions. Within the micro-sprayer the shear stress conditions were not known. However, with a rheometer, we measured the fluid characteristics of the gel without Roundup Max® added, as shown in Figure 7.3.

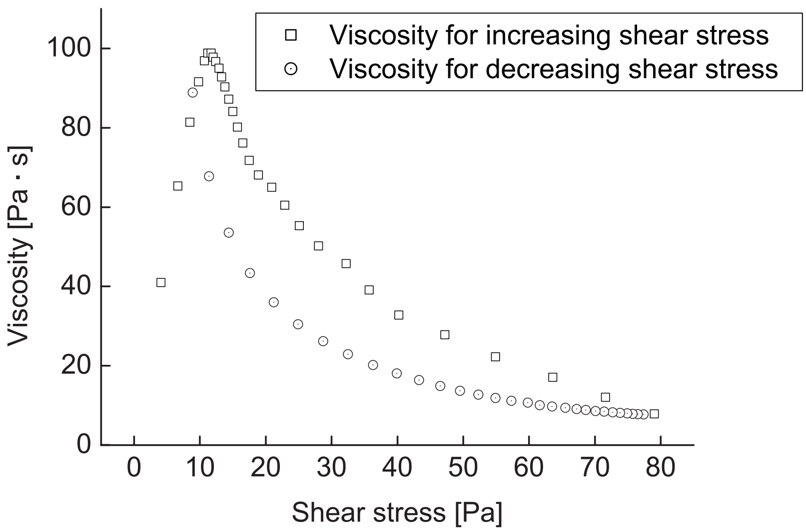

Figure 7.3 Relation between shear stress and viscosity of the gel fluid as used in the micro-sprayer. The relation was measured with a rheometer, the temperature of the gel was 20 °C during the measurement.

In treatment 3, 4, and 5, the flow of the micro-sprayer spraying gel with Roundup Max® added was determined by weighing the mass of 875, 1500, and 3500 droplets respectively. During spraying, the climatic conditions were 20 °C with a relative humidity of 70%. After spraying and a drying period, the plants were transported to the greenhouse where they further grew until the end of the experiment, 28 days after treatment.

(c) Effect parameters: photosynthesis activity, total leaf dry weight, and tuber weight

The photosynthesis activity, leaf dry weight, and the tuber weight were selected as effect parameters of the treatments. Glyphosate is not known to directly interfere with the photosynthesis system of the plants, however its secondary effects on the photosynthesis system of the plants can be determined. In that way the effects of glyphosate on the chlorophyll fluorescence can be recorded a few days after application (Christensen ***et al.***, 2003; Abbaspoor & Streibig, 2005). Chlorophyll fluorescence of the dark adapted plants was determined according to Ketel and Lotz (1997), for which a portable plant photosynthesis meter (Model PPM, EARS, Delft, The Netherlands) was used; photosynthesis activity was derived from the chlorophyll fluorescence according to Franzaring ***et al.*** (2001) and Kempenaar & Lotz (2004). Measurements took place 1, 3, 5, 7, 9, 14, 21, and 28 days after treatment (DAT). The photosynthesis meter showed photosynthesis activity values ranging from 20, indicating dead material with no photosynthesis activity, to 80 and higher, indicating healthy growing plant material. At 14 DAT a response is required from the plants to prevent spread from diseases in a practical field situation. Therefore, the results section focuses on the

14 DAT photosynthesis measurements. At 28 DAT the leaf dry weight of the plants was determined. The samples were oven-dried for a period of 24 hours at a temperature of 85 °C and the total leaf dry weight was expressed in % reduction compared to the control plants. Finally, at 28 DAT the tubers of the plants were harvested and weighed.

(d) Data analysis, statistics and off-target spraying

In this research, five treatments with five doses and 15 replicates were sprayed. This multiplicates to 375 plants. Fifteen plants were not sprayed at all and served as a control for the overall experiment. The effect parameters are presented as graphs based on the doses of 0.0945, 0.338, 0.945, 2.70, and 6.75 kg a.e. ha^{-1} and grouped by treatment 1, 2, 3, 4, and 5. Then, the variation of the effect parameters was evaluated using box-plots. The box itself contains 50% of the data, the mean is represented with a '□', the whiskers represent 90% of the data, the 'x'-markers represent 98% of the data, the '-'markers represent the minimum and maximum values. Individual dose-response curves were fitted, but these were non-significant due to high variability in the responses of the plants within the replicates. Therefore, only ANOVAs and box-plots were used to evaluate trends that were seen in the responses.

Before the plants were sprayed, their ground covered surface area at three weeks after emergence was measured. The ground covered surface area was measured with a VGA resolution camera. Thus, the green pixels could be transformed to square centimeter ground covered surface area. In the experiment, the application rate was not adapted to the ground covered surface area of the plants. However, the ground covered surface area influences the amount of intercepted spray droplets by a plant. Therefore, we included the measured ground covered surface area as a covariate in the analysis of variance (ANOVA) that was used to highlight differences between the mean responses of the five doses and the five treatments.

When switching flat fan nozzles on and off, one can imagine a rectangular block pattern around the targets to be sprayed; the volunteer potatoes. To calculate the amount of off-target spray deposition, a simplified model of a potato plant, a circle was assumed. The area of the circle is equivalent to the ground covered surface area of the potato plants (Figure 7.4 a and b). The vision detection system developed in Nieuwenhuizen ***et al.*** (2008b) will be connected to the sprayers and has centimeter accuracy for detection of volunteer potato plants.

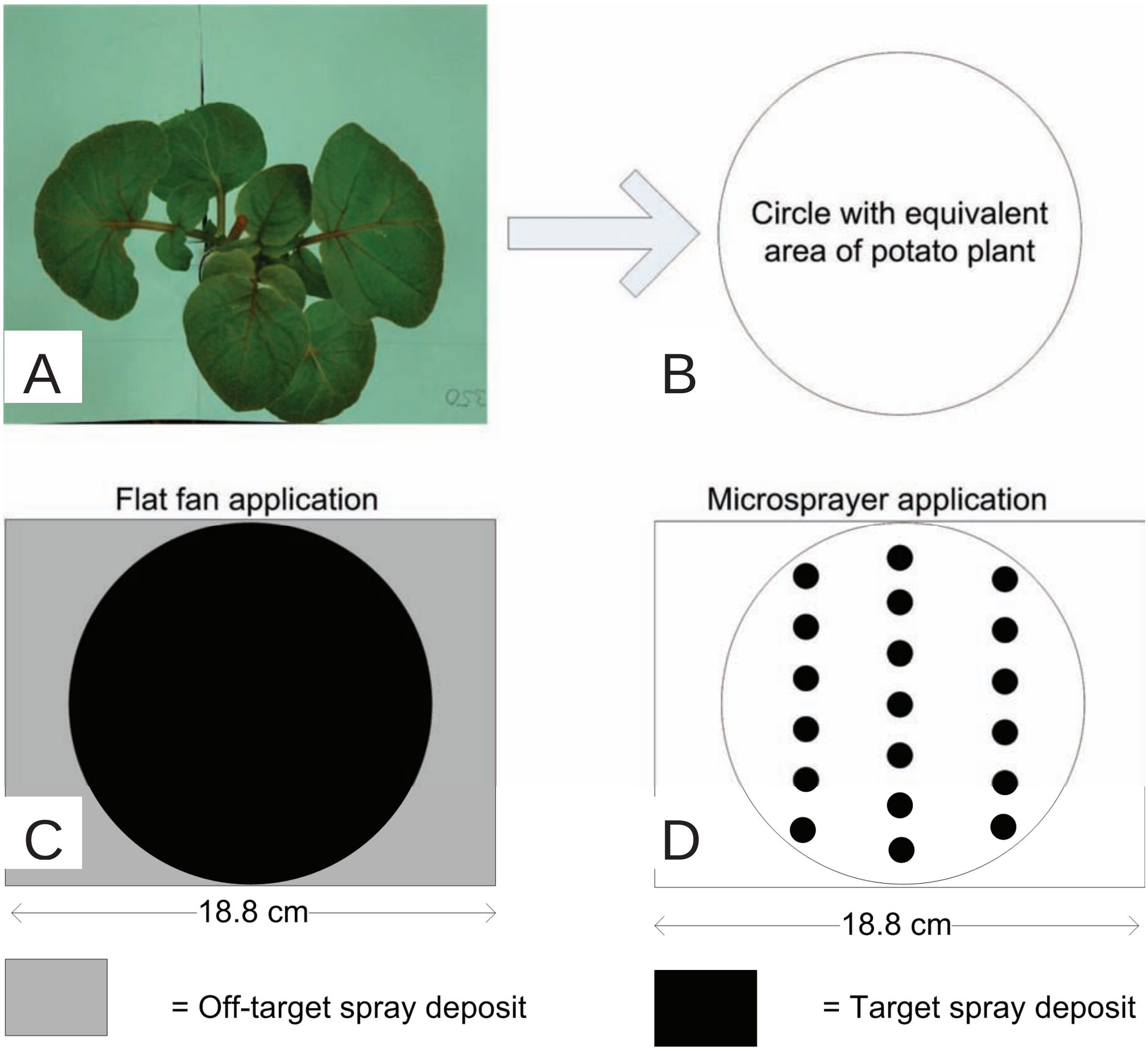

Figure 7.4 Scheme showing calculation of off-target spraying. a) Ground covered surface area determination of potato plant. b) Area is transformed to a circle. c) Flat fan application showing off-target spray deposition. d) Microsprayer application spraying drops on demand within the contours of the plant.

Then, we calculated the amount of spray deposit that would not fall on the target, but besides the targets, both for the flat-fan sprayer and the micro-sprayer (Figure 7.4 c and d). Specifically, an ideal flat fan nozzle that had an even distribution pattern with a width of 18.8 cm, equal to the working width of our micro-sprayer was used. The amounts of off-target spray deposit are presented in the results section.

7.4 Results

Microsprayer droplet masses

The droplet masses measured during the microsprayer treatments are given in Table 7.1. The table shows that for increasing Roundup Max® concentrations the droplet mass increases. The low droplet density pattern having less droplets per unit area had for each concentration larger droplets than the medium density pattern. In addition, the medium density pattern had larger droplets than the high density pattern. So, each pattern produced its own class of droplet masses.

Table 7.1 The density, Roundup Max® concentration, and single droplet mass given per treatment.

Treatment #	Density [droplets m^{-2}]	Roundup Max® concentration [%]	Single droplet mass [mg]
3	676	0.21	19.03
	"Low"	0.75	21.65
		2.1	20.81
		6	20.74
		15	22.39
4	1330	0.21	10.54
	"Medium"	0.75	11.81
		2.1	11.95
		6	12.21
		15	14.17
5	3022	0.21	6.96
	"High"	0.75	7.24
		2.1	8.02
		6	8.63
		15	10.27

Covariate ground covered surface area

Relatively more small plants were present in the experiment as is shown in Figure 7.5. Most of the plants were of the size between 50 and 100 cm^2. The smallest plant had a ground covered surface area of 2 cm^2, the mean was 218 cm^2 and the maximum area was 649 cm^2. Fifteen plants had an area below 30 cm^2. These plants were sprayed within treatment 1 and 2 with the flat fan applications. The smallest plant that was sprayed with the micro-sprayer was 34 cm^2. All the plants that were micro-sprayed were visually inspected and it was confirmed that they received their glyphosate dose.

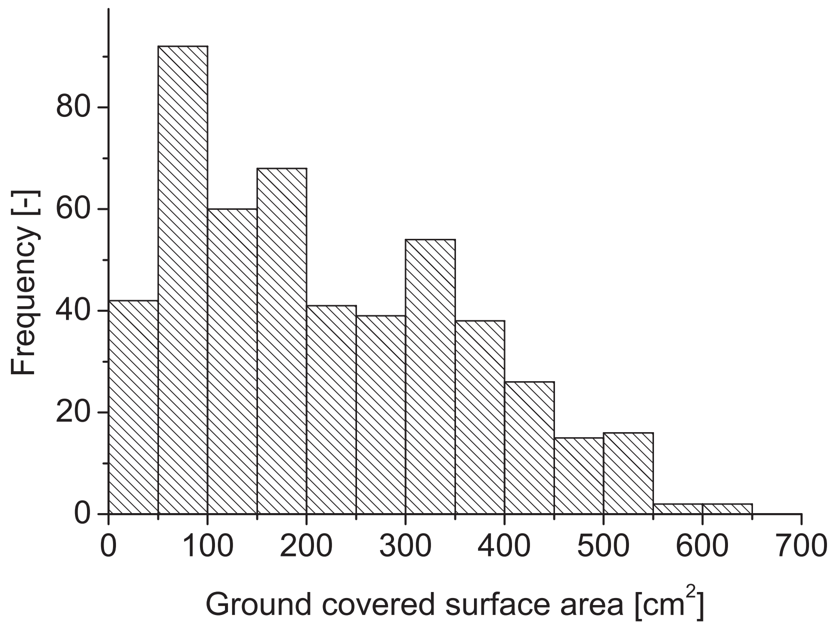

Figure 7.5 Histogram shows the frequency of plants with a certain ground covered surface area in cm^2 as was measured with a camera just before spraying.

Photosynthesis activity at 14 DAT

The box-plot in Figure 7.6a shows that a decrease in photosynthesis was observed for increasing dose. The highest dose of 6.75 kg a.e. ha^{-1} did not result in complete reduction of photosynthesis activity at 14 DAT. Plants still showed photosynthesis activity higher than 20 at 14 DAT. Figure 7.6b shows a large spread in observed data between the treatments.

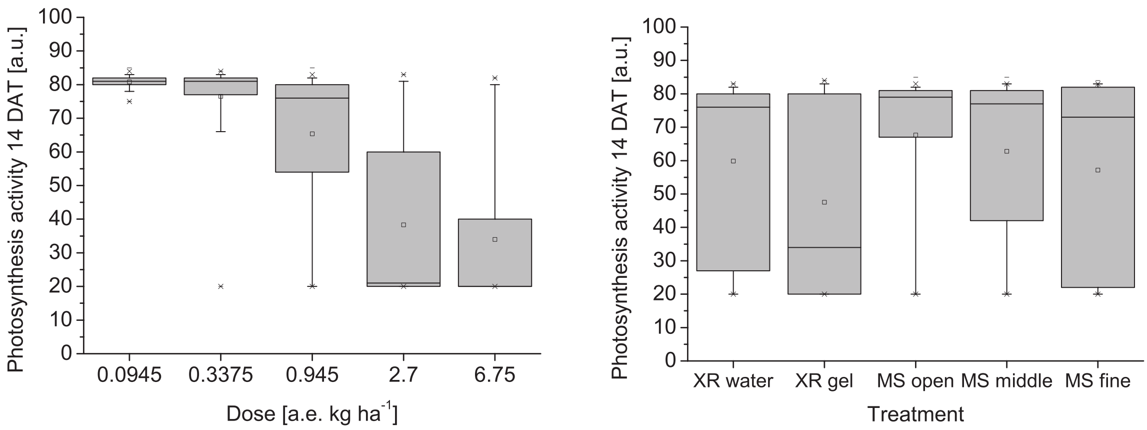

Figure 7.6 a) Boxplot shows the photosynthesis activity 14 DAT of the plants for each concentration b) Boxplot shows the photosynthesis activity 14 DAT of the plants for each treatment. The mean is represented with a ‘□’, the whiskers represent 90% of the data, the ‘x’-markers represent 98% of the data, the ‘-’markers represent the minimum and maximum values.

The flat fan gel application shows a lower mean photosynthesis activity value. The covariate ground covered surface area explained a significant amount of the variance in the ANOVA on the photosynthesis activity effect parameter. Application rate, treatment, and their interaction are all significant as shown in Table 7.2. The higher doses show significant different responses compared to the lower doses as shown in Table 7.3. The low density pattern of the micro-spray application had significantly less effect compared to the other treatments that had a higher density pattern on the plants. The high density distribution of the microsprayer had the same effects on photosynthesis activity as the flat fan gel and flat fan water applications.

Table 7.2 Analysis of variance to test significant differences between the main effects of dose, treatment, and interaction terms for the 14 DAT photosynthesis activity effect parameter.

Photosynthesis activity 14 DAT Source	d.f.	F-value	P-value
Ground covered surface area	1	36.21	<.0001
Dose	4	136.50	<.0001
Treatment	4	12.32	<.0001
Dose × treatment	16	3.17	<.0001

Table 7.3 Post Hoc t-test for significant differences between mean responses in photosynthesis activity for both dose and treatment as grouping variable. Different characters per grouping indicate significant different responses ($\alpha = 0.05$).

Photosynthesis activity [a.u.]					
Grouped by Dose [a.e. kg ha^{-1}]	Mean		Grouped by Treatment	Mean	
0.0945	80.80	A	XR water	59.85	BC
0.3375	76.53	A	XR gel	47.51	C
0.945	65.39	B	MS low	67.68	A
2.7	38.32	C	MS medium	62.80	AB
6.75	33.96	C	MS high	57.16	C

Total leaf dry weight

The total leaf dry weight shows a decrease for an increase in dose shown in Figure 7.7a. Grouped by treatment (Figure 7.7b), the responses are quite evenly distributed, between 30 and 50%.

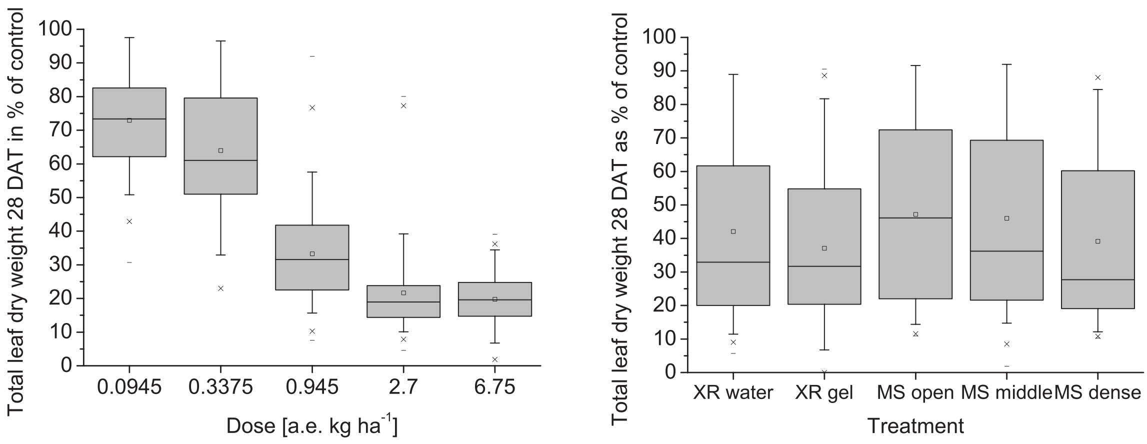

Figure 7.7 a) Boxplot shows the percentage of total leaf dry weight 28 DAT compared to the control of the plants for each concentration b) Boxplot shows the percentage of total leaf dry weight 28 DAT compared to the control of the plants for each treatment.

The effect of the covariate ground covered surface area was not significant (Table 7.4). The dose and the type of sprayer and its interaction had significant effects on the response variable total leaf dry weight. An increasing dose resulted in a lower percentage total leaf dry weight.

Table 7.4 Analysis of variance to test significant differences between the main effects of dose, treatment, and interaction terms for the total leaf dry weight effect parameter.

Total leaf dry weight			
Source	d.f.	F-value	P-value
Ground covered surface area	1	0.35	0.5567
Dose	4	222.14	<.0001
Treatment	4	7.78	<.0001
Dose × treatment	16	1.90	0.0192

Table 7.5 Post Hoc t-test for significant differences between mean responses in total leaf dry weight for both dose and treatment as grouping variable. Different characters per grouping indicate significant different responses (α = 0.05).

Total leaf dry weight as percentage of control [%]					
Grouped by Dose [a.e. kg ha^{-1}]	Mean		Grouped by Treatment	Mean	
0.0945	72.93	A	XR water	42.08	BC
0.3375	63.95	B	XR gel	37.09	D
0.945	33.28	C	MS low	47.21	A
2.7	21.66	D	MS medium	46.03	AB
6.75	19.76	D	MS high	39.16	CD

The Post Hoc t-test (Table 7.5) shows that the low density pattern of the micro-spray application gave significantly less control at 47%, compared to the high density pattern of the micro-sprayer (39%) and the flat fan application with gel (37%).

Tuber weight

Higher doses resulted in lower yield for tuber weight of the potato plants, as shown in Figure 7.8a. The higher doses resulted in tuber yields close to zero, however with some extreme observations showing a high tuber yield. Figure 7.8b shows that the treatment was not of influence on the final tuber yield.

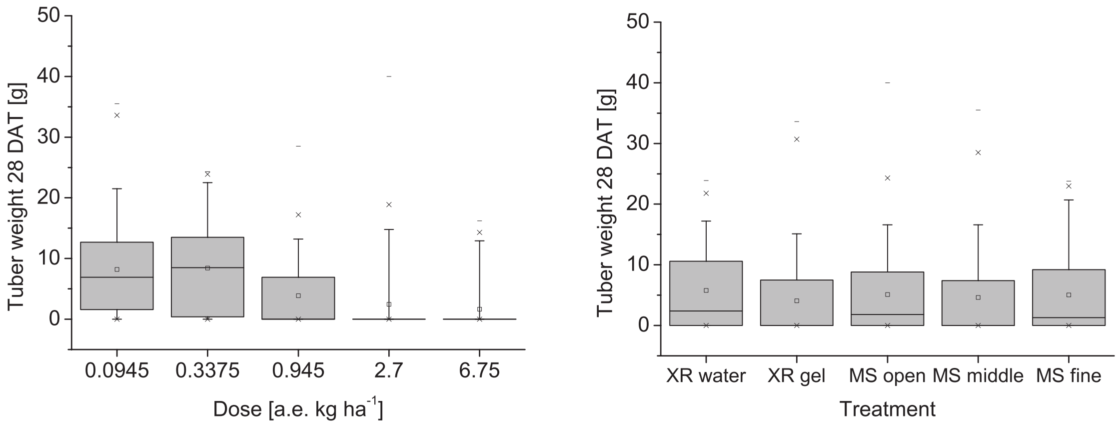

Figure 7.8 a) Boxplot shows the tuber weight 28 DAT of the plants for each dose b) Boxplot shows the tuber weight 28 DAT of the plants for each treatment.

The covariate ground covered surface area as well as the treatment were not significant in the ANOVA shown in Table 7.6. The dose and the interaction between treatment and application rate explained a significant amount of the variance. Higher doses gave lower tuber yield. The two low doses combined gave a tuber yield of 8.3 g plant^{-1}. The two highest doses gave a tuber yield of 2.1 g plant^{-1}. The treatment had no influence on the obtained tuber yield, see Table 7.7

Table 7.6 Analysis of variance to test significant differences between the main effects of dose, treatment, and interaction terms for the tuber weight effect parameter.

Tuberweight Source	d.f.	F-value	P-value
Ground covered surface area	1	4.64	0.0319
Dose	4	19.64	<.0001
Treatment	4	0.47	0.7598
Dose × treatment	16	2.47	0.0014

Table 7.7 Post Hoc t-test for significant differences between mean responses in tuber weight for both dose and treatment as grouping variable. Different characters per grouping indicate significant different responses (α = 0.05).

Tuberweight [g]					
Grouped by Dose [a.e. kg ha^{-1}]	Mean		Grouped by Treatment	Mean	
0.0945	8.19	A	XR water	5.78	A
0.3375	8.42	A	XR gel	4.06	A
0.945	3.88	B	MS low	5.10	A
2.7	2.45	CB	MS medium	4.61	A
6.75	1.65	C	MS high	5.02	A

Off-target spraying with flat fan nozzles

In the ideal situation of a flat fan nozzle with an even distribution and a working width of 18.8 cm, the following off-target spray percentages were found for the flat fan applications. A small sized plant with diameter 12.2 cm shows 95% off-target, a medium sized plant with diameter 15.8 cm 50% off-target and a large plant with diameter 18.8 cm gives 27% off-target spray application respectively. So, smaller plants show higher amounts of off-target spraying. However, our micro-sprayer is able to turn on and off individual needles in a drop-on-demand fashion that serves contour following of the weed plants and does not show any off-target spraying.

7.5 Discussion

The ground covered surface area was introduced as a covariate in the analysis of variance. The ground covered surface area relates to the leaf area index as reported by Boyd ***et al.*** (2002). This means that the spray droplet interception of the plants is related to the ground covered surface area of the plants as well. The differences in responses of the effect parameters reported are therefore valid for the range of ground covered surface areas that we measured during the experiment.

The plants in our experiment were greenhouse grown potato plants. To grow these plants, the tubers were treated with gibberellic acid to break their dormancy. However, Lovell and Booth (1967) reported that gibberellic acid affects the growth of the potato plants and the shoots as well, especially the tuber formation process as reported by Rehman ***et al.*** (2001). However Rehmans dose of 1000 ppm is way higher compared to the dose of 1 ppm used just for breaking the dormancy in this experiment. Our dose of gibberellic acid used is supposed not to influence the shoot growth as it is much lower than the applied dose reported by Rehman ***et al.*** (2001). Due to the gibberellic acid effects, we do not draw conclusions from the effects of the tuber weight that we have measured in our experiment. Another factor influencing potato plant growth is the application of low doses of glyphosate. For example, Lutman and

Richardson (1978) reported that low application rates of glyphosate stimulates the formation of a large number of tubers. Although for practical situations in the field, the inhibition of tuber production is required. Finally, the photosynthesis activity and the total leaf dry weight are good indicators of the quality of the treatment, as these parameters show how well, and how fast in time the control action worked on the plants. Though, the available data did not allow a full statistical dose response analysis, results indicate the following doses reached ED_{90} according to visual inspection of the box-plots. For photosynthesis activity 14 DAT, total leaf dry weight, and tuber weight the doses were 6.75, 2.7, and 2.7 a.e. kg ha^{-1} respectively. This indicates that when a sufficient amount for reduction of photosynthesis at 14 DAT is applied, that leaf dry weight and tubers will be controlled as well.

The effects of the droplet distribution patterns showed that the higher density patterns had a higher efficacy compared to the patterns with lower density. This holds for the droplet sizes used in our micro-spray experiment that range between 2400 and 3400 µm, which is 5 to 10 times larger compared to the droplet sizes sprayed from flat fan nozzles with volume mean diameters of 200 to 600 µm (Etheridge ***et al.***, 1999). According to Etheridge ***et al.*** (2001), the effect of droplet size on herbicide efficacy depends on a number of factors, with the specific herbicide and plant species being most critical. In literature inconsistent results are reported as applying glyphosate at a constant concentration in large rather than small droplets reduced glyphosate efficacy (Boerboom & Wyse, 1988) and increased (Graglia, 2004) glyphosate efficacy. It is generally assumed that efficacy of contact herbicides may be more adversely affected by increasing droplet size than systemic herbicides such as glyphosate. However, in our research we observed that the low density pattern did not increase the efficacy but reduced the efficacy of glyphosate. Research until now was always done with water based spray solutions. In contrast, in this research the spray fluid was a gel. Probably there is an optimum in uptake to the total leaf with regard to the droplet size and droplet fluid characteristics, somewhere between the small droplets deposited from the microsprayer and the larger droplets sprayed with a flat-fan nozzle.

The herbicide savings between 27 and 95% that are claimed in this work are under the assumption of circular morphology of plants when viewed from above. The plants are situated under the center of the sprayer as well. Therefore, actual savings and efficacy of the treatment will differ in a field situation where plants are not always centered under the microsprayer or flat fan nozzles. A field experiment will give more insight into the actual abilities of volunteer potato plant specific application of glyphosate. In general, we should keep in mind that flat fan nozzles can never follow the contours of the plants. However our micro-sprayer features a drop-on-demand system that is able to follow the contours of weed or crop plants and is able to deposit larger droplets at places where deposits are actually required, and not onto the soil with unwanted run-off as a result. The micro-sprayer is connected to a machine vision system that enables individual needle control, and individual droplets can be targeted on the volunteer potato plants (Nieuwenhuizen ***et al.***, 2008a) with centimeter precision detection and control (Nieuwenhuizen ***et al.***, 2008b). Therefore a better efficiency of the applied herbicides is always expected for a micro-sprayer or drop on demand system.

The further perspectives for the application of micro-sprayer systems for control of weeds in agricultural fields are promising. However, some steps have to be made before the systems can be adopted in practice. For example, the fluid characteristics should be measured together with Roundup Max® concentrations, as the adjuvants and surfactants in the formulation influence the shear stress and viscosity. The micro-sprayer droplet masses increased when the Roundup Max® concentration increased in the gel. This is due to the changed fluid characteristics when adding Roundup Max®. Calculation and determining the shear stress conditions within the micro-spray system to predict the desired settings of the system will improve the performance of the system. Bergeron ***et al.*** (2000), Bergeron (2003) and Williams ***et al.*** (2008) showed that with what Bergeron called 'intelligent fluids' the splash effects of larger spray droplets can be reduced tremendously. This would allow the production of suitable droplets for use with micro-sprayers. This is part of our research project investigating the droplet formation on the micro-sprayer.

7.6 Conclusions

Photosynthesis activity measurements showed no significant difference between the flat fan water (exp. 1) and flat fan gel (exp. 2) application of glyphosate on the volunteer plants. The total leaf dry weight was significantly ($\alpha = 0.05$) lower at 37% for the flat fan gel application compared to the flat fan water application that gave 42% of the weight of the control.

The photosynthesis activity values of the micro-sprayer low and medium density pattern, 68 and 63 respectively, were higher compared to the flat fan gel application and micro-sprayer high density pattern, 48 and 57 respectively. The total leaf dry weight was higher for the low and medium density pattern of the microsprayer, with a reduction of 47% and 46% respectively, compared to the flat fan gel application and the micro-sprayer high density pattern, with a reduction of 37% and 39% respectively.

The high density distribution pattern of 3022 droplets m^{-2}; 3.30 mg $droplet^{-1}$ had a better efficacy for both photosynthesis activity as well as for control of the total leaf dry weight. Furthermore, no significant differences were found between the low density (676 droplets m^{-2}; 14.78 mg $droplet^{-1}$) and medium density (1330 droplets m^{-2}; 7.52 mg $droplet^{-1}$) pattern of the micro-sprayer.

It is possible to destroy volunteer potato plants with glyphosate in gel with the three patterns used. The patterns of 676, 1330, and 3022 droplets m^{-2} destroyed the plants and resulted in reduced total leaf dry weight and tuber weight. In addition, a micro-sprayer is in favor of a flat fan application in that it follows the contours of a plant as it is a drop on demand system. Therefore, it eliminates unwanted runoff and the applied amounts of active ingredients per unit area are better used. For the plant sizes sprayed in our experiment the herbicide savings of a micro-sprayer compared to an on-off switching flat fan nozzle ranges from 27% to 95%.

7.7 Acknowledgements

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Chapter 8

Performance evaluation of an automated detection and control system for volunteer potatoes in sugar beet fields

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8.1 Abstract

Incomplete control of volunteer potato plants causes a high environmental load through increased crop protection chemical usage in potato cropping. A joint effort of industry, policy makers and science initiated a four year scientific project on detection and control of volunteer potato plants. A proof of principle machine for automated detection and control of volunteer potato plants in sugar beet fields has been tested in experimental fields. Machine vision based detection at cm^2 precision is combined with a micro-sprayer with five needles and a working width of 20 cm. The accuracy of the system was ±1.4 cm in longitudinal direction and ±0.75 cm in transversal direction. The main error source was the variability in micro-sprayer droplet velocity that caused longitudinal errors. However, volunteer plants with a size larger than 12 cm^2 were successfully controlled at velocities up to 0.8 m s^{-1}. The approximated capacity of the proof of principle machine is 2.5 hrs ha^{-1}, which is an advancement in the order of one magnitude compared to the current control practices of band sprayers and manual control.

8.2 Introduction

Volunteer potato plants are a major problem in arable farming in the Netherlands and mild climate regions where potatoes are grown. Not only because weed potato plants compete with the crops grown, but also because weed potato plants are a source of spread of diseases, nematodes, and pests (Turkensteen ***et al.***, 2000; Boydston, 2001; Boydston & Seymour, 2002). These are unwanted effects and therefore the adequate control of volunteer potato plants is required. This is stressed by the statutory obligation in the Netherlands under which farmers have to remove these volunteer plants from their fields before the 1st of July in the growing season (Kienhuis & Berge, 2003). Otherwise the weed potato plants could become a too high risk for spread of diseases, nematodes, and pests, causing a high environmental load for the successive crop protection chemicals that are used to overcome its consequences. Current control practices are partial mechanized partial manual application of glyphosate onto volunteer plants. However, the control labor demand of up to 20 hrs ha^{-1} and its related costs are too high for arable farmers, which results in incomplete control (Paauw & Molendijk, 2000). As a result, the stakeholders – farmers, researchers, policy makers – proposed to work on an automated system for detection and control. Although, a detection and control system is a complicated system, especially when the measurement system is a vision system that has to operate together with biological objects in an arable field and in real-time conditions. Therefore, it is a challenge to have the system meeting the expectations of the users.

The objective of this research is to quantify the performance of the proof of principle machine for volunteer potato control in arable field conditions. So, the following topics are discussed in this paper: a) the program of requirements of the users, b) the setup of the hardware and software, and c) the performance of the system.

The main research question was formulated as: Is the performance of the system within the limits of the program of requirements. Specifically:1) What is the biological efficacy of the system in arable field conditions? 2) What is the accuracy of the application of glyphosate of the detection and control system?

8.3 Material and methods

Program of requirements

The program of requirements for detection and control of volunteer plants was defined together with the stakeholders during the fist phase of the research project. In that phase a methodic design approach to engineering was applied (Roth, 1981; Kroonenberg & Siers, 1998) and the result of the problem definition phase is the program of requirements of the integrated detection and control system shown in Table 8.1.

Table 8.1 Program of requirements for the integrated system of volunteer potato detection and control.

	Requirement
1	resolution of detection at least at 2x2 mm (4 mm^2)
2	work under variable natural light conditions
3	resolution of control at least at 10x10 mm (100 mm^2)
4	glyphosate application targeted on volunteer plants only
5	driving speed up to 2 m s^{-1}
6	control of volunteer plants > 95 %
7	undesired control of sugar beet plants < 5 %
8	working width between 15-23 cm; within the sugar beet crop seed line
9	modular system, applicable on 3, 6, or 12 rows of sugar beet plants
10	machine has to work attached to a tractor
11	integration with existing mechanical weeders as an add-on would be preferred

Automated system for detection and control

The automated system consists of a camera detection system, a real-time computer, and a micro-sprayer. These components are linked together and exchange information as shown in Figure 8.1.

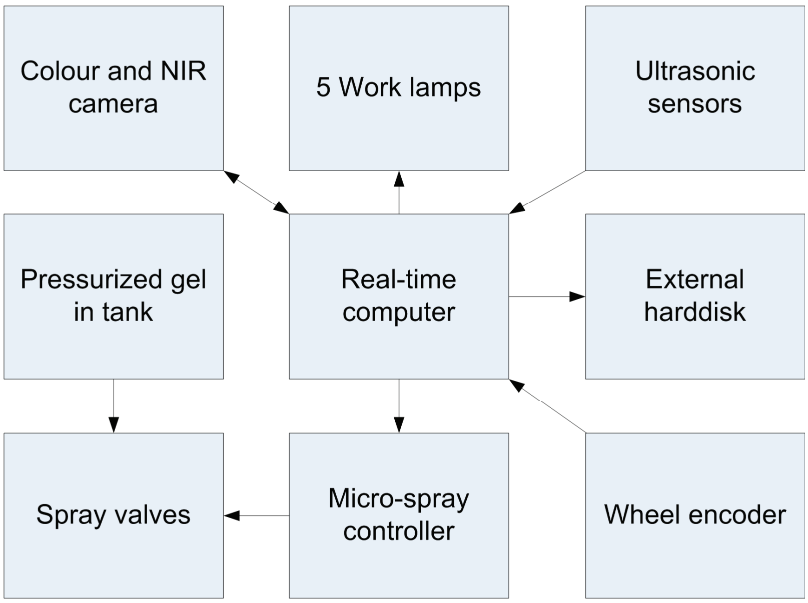

Figure 8.1 Schematic overview of the system components. The arrows indicate the uni- or bidirectional connections between the system components.

The system worked in controlled light conditions. A wheel encoder measured the distance travelled and triggered the cameras and the micro-sprayer. Figure 8.2 (a) shows the system in practice and Figure 8.2 (b) shows a schematic drawing of the compact construction and the position of the sensors and actuator on the construction hinged behind the tractor.

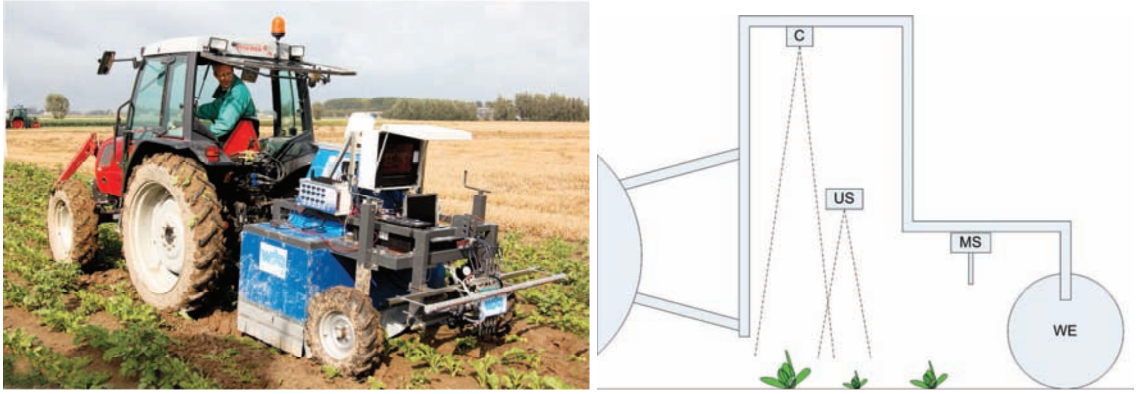

Figure 8.2 Measurement setup in arable field conditions. Two cameras and five xenon work lamps are located under the blue cover with grey plastic flaps. On the system two cameras (C), ultrasonic sensors (US) the microsprayer (MS) and wheel encoder (WE) are connected. The microsprayer consists of five needles and has a working width of 20 cm.

Real-time vision detection

Two cameras (Marlin F201, AVT, Stadtroda, Germany) were used that imaged a ground covered surface area of 150 cm width and 20 cm length (1628*198 pixels). One camera was an RGB camera, the other was a black and white camera that was fitted with a visible light block filter and measured light reflectance in the near infrared wavelengths. Triggering of the cameras was done with a wheel encoder and the controlled light conditions were achieved with help of five xenon work lamps. The images were processed on a 2.2 GHz real time PXI computer (National Instruments, Austin, TX, USA). The image processing consisted of the following steps. First vegetation was detected with an excessive green threshold (Woebbecke ***et al.***, 1995). Second, crop rows were detected with a histogram based approach (Tillett ***et al.***, 2002) and a Kalman filter (Gelb ***et al.***, 1974). Third, colour features were extracted for square centimeter grid cells. An advancement of this method over existing from literature is that occluding plants and connected vegetation are not a problem in the algorithm used in this research. Fourth, a Bayesian classifier was trained. Class A were the weed potato plants and class B were the sugar beet plants. Fifth, grid cells were classified within the crop seed line and in the sixth step plant objects smaller than 12 cm^2 were filtered. Smaller plants were not sprayed due to ineffective uptake of glyphosate (Smid & Hiller, 1981). Finally, the classification result was translated into a spray decision, taking into account the distance between camera and sprayer, and the height of the crop. One droplet was deposited on each 1x4 cm volunteer potato plant area, the area between the rows was also marked for spraying when volunteer plants were present, however no actuator was present between the crop rows. Details of the adaptive detection algorithm are described in Nieuwenhuizen ***et al.*** (2008b).

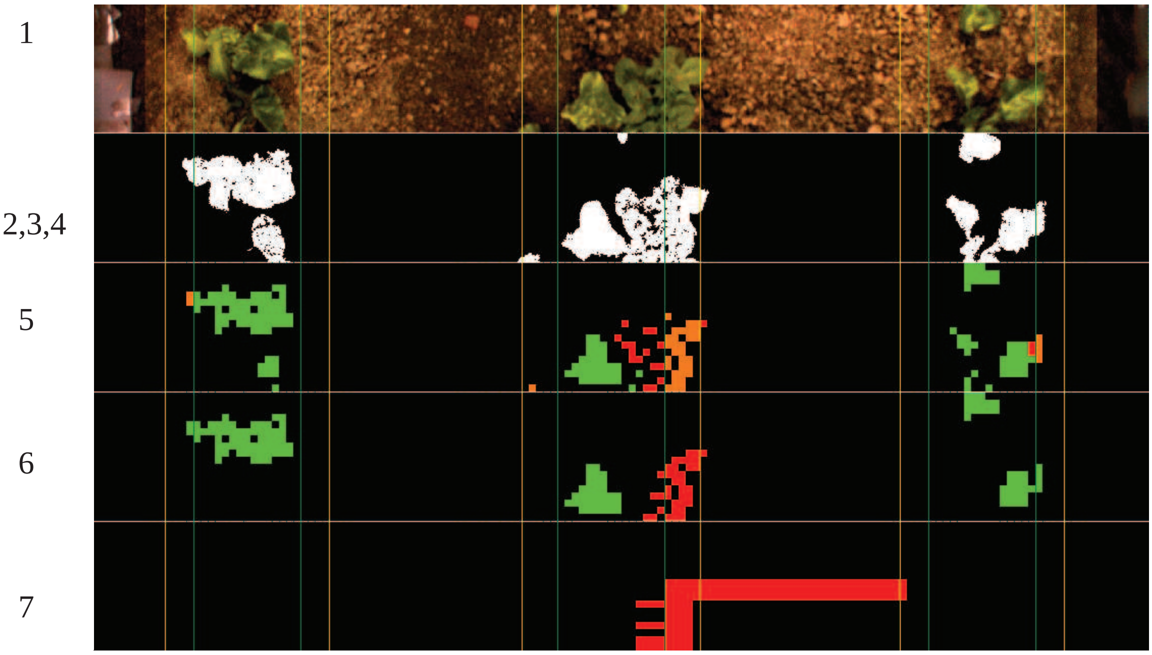

Figure 8.3 Image processing steps. Top image dimensions are 150 cm width and 20 cm length, three sugar beet rows with a row spacing of 50cm are in the field of view. 1) colour image is recorded 2, 3, 4) vegetation and crop rows are detected, colour features extracted, and classifier is trained 5) vegetation is classified 6) small plants are filtered 7) spraying decision are made.

Micro-sprayer system

The micro-sprayer consisted of five needles that were spaced 4 cm apart to ensure a coverage of 20 cm above a crop seed line (Figure 8.4). The needles of the micro-sprayer were fixed at a height of 30 cm above soil level. A pressurized tank (7.5 L at 2.5 bar) was filled with a gel fluid (Agritechnics, Doetinchem, The Netherlands) and connected to the needles through hoses and five fast acting valves. The real-time operating system sent pulse width modulated signals to the individual valves when they had to be operated. This resulted in 20±5 μL droplets released from one to five needles. The maximum frequency at which these droplets were well-formed was 80 Hz. As a consequence this limited in our situation the travel velocity to 0.8 m s^{-1}, as it was required to have a droplet positioning resolution of one droplet per cm in the travel direction. The micro-spray system is described in detail in Nieuwenhuizen ***et al.*** (2008a).

The two-dimensional areas where spray droplets require to be deposited is known from the camera system. However, released droplets have to travel through the air medium to the plants for a distance $\boldsymbol{d_z}$ (Figure 8.4). Therefore, in addition to the 2-dimensional information, the height of the plants is required as well to correctly position the droplets on the plants. When droplets were formed they received an initial velocity $\boldsymbol{v_{zd}}$. The height distance $\boldsymbol{d_z}$ between micro-sprayer needle and plant was measured with three ultrasonic sensors (LV-MaxSonar-EZ1, Maxbotix, Tucson, AZ, USA) above each crop row. Based on the distance to the plants, the microsprayer droplet speed $\boldsymbol{v_{zd}}$, and the travel speed $\boldsymbol{v_{xp}}$, droplets were released from the micro-sprayer a certain distance in advance of the actual pass of the microsprayer. So $\boldsymbol{d_x}$ is a function of $\boldsymbol{v_{xp}}$, $\boldsymbol{v_{zd}}$ and $\boldsymbol{d_z}$ and is shown in Equation (8.1).

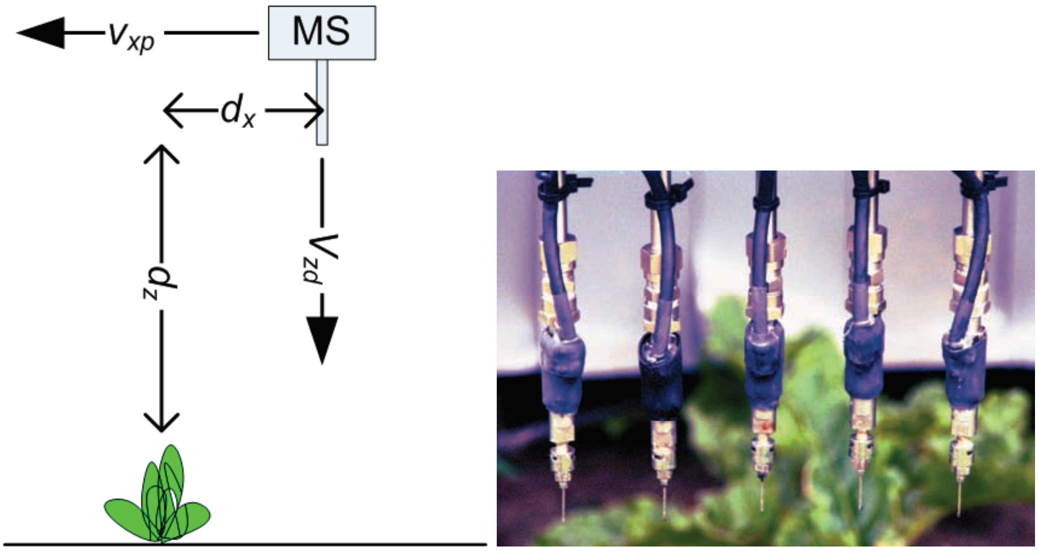

Figure 8.4 Schematic of the micro-sprayer (MS) above the weed potato plants to be sprayed. The micro-sprayer is connected to the platform as shown in (B) and moves forward with platform velocity in x-direction $\boldsymbol{v_{xp}}$. The droplets released from the micro-sprayer have a velocity in the z-direction $\boldsymbol{v_{zd}}$. The vertical distance between needle and weed potato plant is $\boldsymbol{d_z}$. The droplet release distance in travel direction is $\boldsymbol{d_x}$.

$$\boldsymbol{d}_x = \frac{\boldsymbol{v}_{xp}}{\boldsymbol{v}_{zd}} \boldsymbol{d}_z \tag{8.1}$$

In our experiments we assumed a momentary constant travel velocity for each image that was processed. The travel velocity $\boldsymbol{v_{xp}}$ was updated each wheel encoder pulse but was sampled by the processing software once for each 20 cm length of an image. The micro-sprayer droplet release velocity $\boldsymbol{v_{zd}}$ was measured in advance of the experiments and was 2.0±0.2 m s^{-1} and was therefore set at 2.0 m s^{-1} in the model. Before the experiments were carried out, the mechanical setup of the detection and control system was calibrated under static conditions. Specifically, the distances between camera, sprayer and ultrasonic sensors were measured. The distances were input to the real-time processing software. The wheel encoder was also calibrated for use in field conditions.

Field-test and biological efficacy on volunteer plants

Two experimental fields were used to detect and spray volunteer potato plants. One field was on a sand soil, the other field was on a clay soil, both near Wageningen, the Netherlands. The length of the fields on sand and clay soil was 150 m and 105 m respectively. The volunteer plants were sprayed with a 5% glyphosate (Roundup Max, 450 g L^{-1}, Monsanto, City, Country) solution in gel fluid. The fluid was colored with the solvent black dye nigrosine, to trace the droplets in the field after spraying. Targeted droplets were released on each 1 x 4 cm area of volunteer potato plant area that was detected, see Figure 8.3, step 7. The fields were split into three sections that were travelled with 0.2, 0.4, and 0.8 m s^{-1} (Figure 8.5). The experiment was carried out on the 13th of October 2008. The field situation was a 79.4% seed emergence rate at the sand soil and 50.9% seed emergence rate at the clay soil, relatively low caused by the autumn season. After the experiment, the number of plants in the field was counted and the numbers hit and missed plants were counted and are presented. Two weeks after spraying the plants were examined again and the biological efficacy was scored on a binary scale: full control or not controlled at all.

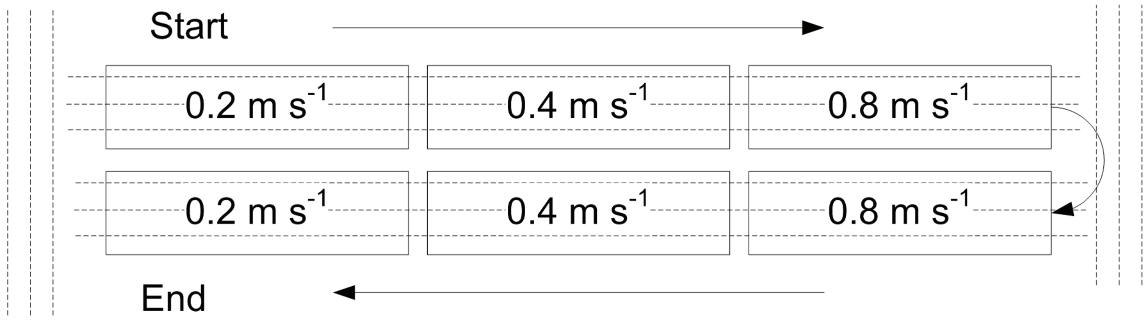

Figure 8.5 Schematic of the experimental field. Sugar beet rows are indicated with - - - - . Travel velocity was increased while driving in one direction and was decreased while travelling back. Three sugar beet rows were covered by the system. The headlands were not used during the experiment.

Precision evaluation test

In addition to the biological efficacy tested in the field, the precision and accuracy of the integrated vision and micro-sprayer system was evaluated. In an experiment, green paper targets were detected and sprayed. The travel velocity in the experiment was equal to the field test and was 0.2, 0.4, and 0.8 m s^{-1} . The height of the targets was 0, 5, 10, 15, and 20 cm and five successive targets were placed on the same height. So, one series consisted of 25 targets (Figure 8.6). At a certain travel velocity a series was repeated three times. This procedure was followed for triangular and circular targets with an area of 162 cm^2 and 254 cm^2 respectively. Thus, in total 450 targets were sprayed. Circular targets were chosen to mimic the shape of the plants. The triangular targets were chosen to challenge the system on straight and skew edges. A schematic of one spraying series is shown in Figure 8.6. The distances between the targets were sampled from a uniform distribution between 18 and 36 cm, to prevent aliasing effects between the detection system that was triggered each 20 cm and the size of the target objects whose length was 18 cm. A space of 90 cm was kept between the groups of five targets.

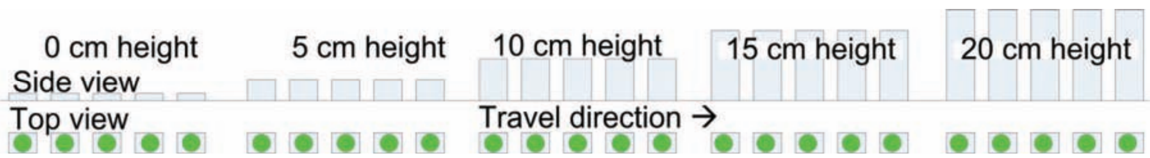

Figure 8.6 Experimental setup during accuracy testing of the precision spraying equipment. The top-view shows the position of the 254 cm^2 circles on A4-paper (21x29.7cm) that were used as targets.

During the experiment, the sensor data of the detection system was processed into actuator signals for micro-sprayer actuation. All the processed sensor data were recorded on hard disk and were analyzed off-line after the experiment as well. The green paper targets that were sprayed in the experiment were collected after the experiment and were scanned with a flatbed scanner at 300 dpi (Figure 8.7). Now, the difference between the stored processed images and the scanned images of the sprayed paper targets were used to asses the accuracy of the system.

The accuracy is presented as the number of droplets sprayed inside and outside the target, and the deviation in longitudinal and transversal direction from the desired position. The size of the stored processed targets and of the scanned sprayed targets is presented as well, as a discrepancy between the sizes could explain the accuracy that was achieved. The sizes are given as a ratio; the 'processing detection size factor' is $\boldsymbol{A}_{processing}/\boldsymbol{A}_{scanned}$ and the 'spray cells size factor' is $\boldsymbol{A}_{spraycells}/\boldsymbol{A}_{scanned,}$ where $\boldsymbol{A}$ equals the area. $\boldsymbol{A}_{processing}$ is the area that was determined in step 6 of the image processing. $\boldsymbol{A}_{spraycells}$ is the area that was determined in step 7 of the image processing (Figure 8.3).

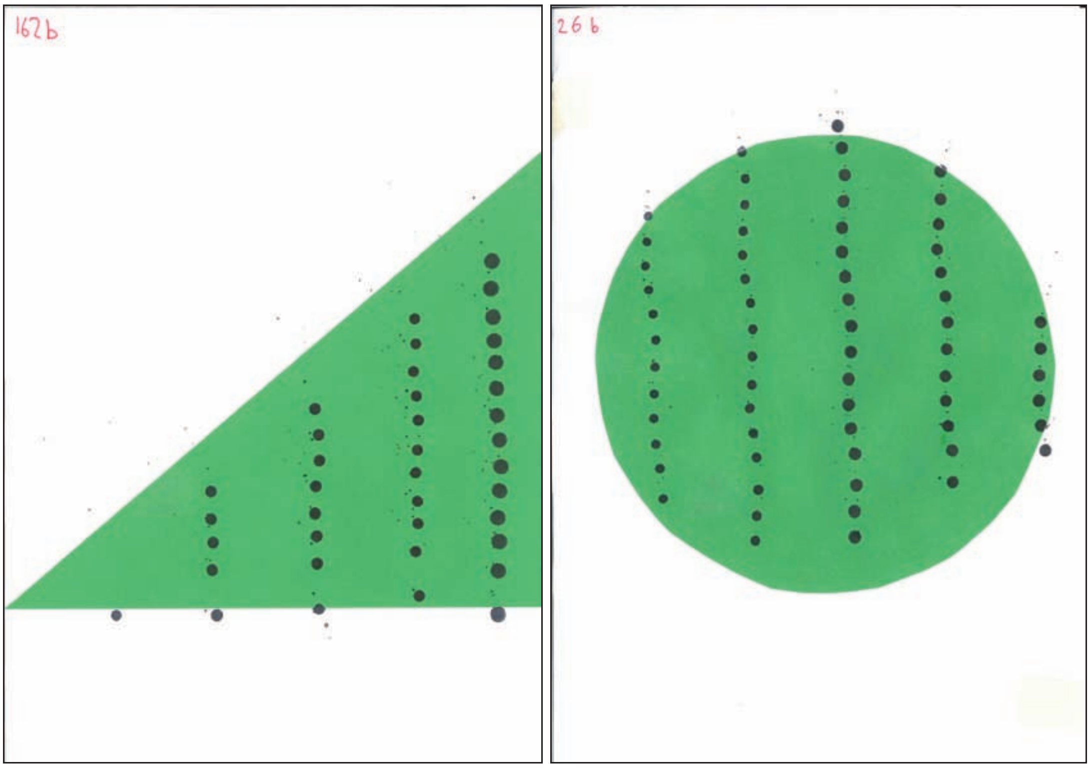

Figure 8.7 Example scanned image of sprayed triangle (a) and circle (b). Five rows of droplets were sprayed. The targets were placed on A4 paper (21x29.7 cm)

8.4 Results and discussion

Field-test and biological efficacy

Table 8.2 shows the total number of sugar beet and potato plants, the plants that were hit and missed, and the percentage of plants that was sprayed in the field-test on both the sand and clay soil. Comparing the results at the sand soil and the clay soil, Table 8.2 shows that the results were better at the sand soil. This is probably due the better seed emergence rate at the sand soil.

Table 8.2 Number of sprayed sugar beet and volunteer potato plants at different velocities. Two experimental fields were used: sand and clay soil. The plants were counted directly after spraying.

sand soil	sugarbeet			volunteer potato		
velocity, m s^{-1}	total	hit (%)	missed (%)	total	hit (%)	missed (%)
0.2	217	3 (1.4)	214 (98.6)	25	23 (92.0)	2 (8.0)
0.4	208	2 (1.0)	206 (99.0)	30	26 (86.7)	4 (13.3)
0.8	195	1 (0.5)	194 (99.5)	18	15 (83.3)	3 (16.7)
0.8	174	2 (1.1)	172 (98.9)	25	21 (84.0)	4 (16.0)
0.4	191	1 (0.5)	190 (99.5)	19	17 (89.5)	2 (10.5)
0.2	206	0 (0.0)	206 (100.0)	11	11 (100.0)	0 (0.0)
total	1191	9 (0.8)	1182 (99.2)	128	113 (88.3)	15 (11.7)

clay soil	sugarbeet			volunteer potato		
velocity, m s^{-1}	total	hit	missed	total	hit (%)	missed (%)
0.2	101	1 (1.0)	100 (99.0)	10	10 (100.0)	0 (0.0)
0.4	78	0 (0.0)	78 (100.0)	14	13 (92.9)	1 (7.1)
0.8	70	0 (0.0)	70 (100.0)	15	12 (80.0)	3 (20.0)
0.8	91	0 (0.0)	91 (100.0)	12	9 (75.0)	3 (25.0)
0.4	90	0 (0.0)	90 (100.0)	14	11 (78.6)	3 (21.4)
0.2	104	1 (1.0)	103 (99.0)	19	17 (89.5)	2 (10.5)
total	534	2 (0.4)	532 (99.6)	84	72 (85.7)	12 (14.3)

With increasing velocity, the percentage of potato plants that was hit decreased. This was measured at both sand and clay soil and while travelling back and forth. This decrease was probably caused by an incorrect micro-spray droplet velocity. In this way droplets were probably released too late and fell behind the potato plants. However, this was not confirmed with a decrease in the number of sugar beet plants that was hit at 0.8 m s^{-1}.

Table 8.3 gives the mortality percentage of sugar beet and volunteer potato plants at the experimental fields at sand and clay soil respectively. The percentage of controlled sugar beet plants 14 DAT, 1.4 and 0.6%, is higher than the number of plants that were identified as being hit directly after spraying.

Table 8.3 Percentage of fully controlled sugar beet and volunteer potato plants 14 days after treatment (DAT).

	percentage of fully controlled plants	
	sugar beet	volunteer potato
sand soil	1.4	82.8
clay soil	0.6	71.2

This was 0.8 and 0.4% for both the sand as well as the clay soil as shown in Table 8.2. Probably, this was caused either by glyphosate being transferred from plant to plant by leaves that have touched each other after spraying or by satellite drift-like droplets that reached sugar beet plants. The sugar beet plants that were controlled were always growing close to the volunteer potato plants that had been sprayed. On the other hand, the volunteer potato plants had a reduced percentage of control. For a volunteer potato plant to be completely controlled, it is required that each stem receives an amount of glyphosate deposited on the leaves. However, 14 DAT it appeared that some plants had not received glyphosate on all stems and were not fully controlled. Therefore, the percentage of controlled volunteer plants 14 DAT decreased compared to the percentage of plants that had been identified as being sprayed directly after the experiment. All the stems that received one or more 20 μL droplets 5% glyphosate were well controlled. This corresponds to Lutman (1978) and Masiunas (1988) who found that application of 5% glyphosate solution controls volunteer plants.

Precision evaluation test

When all the 450 targets of the precision evaluation experiment were combined, 16066 droplets were available for analysis. The mean deviation in longitudinal direction, this is along the travel direction, was 0.41±1.16 cm (Table 8.4). This means that the droplets were on average released 0.41 cm too early, and that some have fallen on the paper surface before the target was reached. The mean deviation in transversal direction, this is perpendicular to the travel direction, was 0.54±0.60 cm. This means that the droplets were on average released 0.54 cm too far to the right compared to the position that was calculated.

The triangles have a larger longitudinal deviation compared to the circles that were sprayed. However, the deviations decreased for increasing travel velocity for both shapes. The decrease in deviation for increase in travel velocity is most likely caused by a deviation of the droplet velocity $\boldsymbol{v_{zd}}$, see equation 8.1. The differences in longitudinal direction between the triangles and circles are most likely caused by the spray cell decision as made by the detection algorithm in step 7 (Figure 8.3). Specifically, when a circle is sprayed the effects on the borders are identical at the top and bottom of the shape, whereas for the triangular shape there is a start effect of the straight edge at the bottom. This may have caused the larger mean deviations in longitudinal direction for the triangles.

With increasing height of the targets, which results in a shorter travel distance of droplets through the air, the mean deviations in longitudinal direction decrease down to a mean deviation of 0.01 cm. However, the standard deviations remain in the same range of 1.06 cm on average, independent of the height. This indicates that other factors than the height influence the positioning accuracy, for example the droplet fall velocity $\boldsymbol{v_{zd}}$.

Table 8.4 Number of droplets and deviations of individual and droplet patterns given for the velocities, shapes and heights during the precision evaluation experiment. The deviations are given in cm with their standard deviation.

				Individual droplets		Droplet pattern	
Velocity m s^{-1}	Target shape	Height m	# of droplets	Longitudinal deviation, cm	Transversal deviation, cm	Longitudinal deviation, cm	Transversal deviation, cm
all	all	all	16066	0.41 ± 1.16	0.54 ± 0.60	0.39 ± 1.40	0.50 ± 0.75
all	circle	all	9858	0.20 ± 1.13	0.36 ± 0.55	-0.03 ± 1.17	0.19 ± 0.38
all	triangle	all	6208	0.76 ± 1.11	0.83 ± 0.55	0.87 ± 1.48	0.84 ± 0.91
0.2	circle	all	3764	0.56 ± 0.93	0.33 ± 0.38	0.58 ± 0.87	0.27 ± 0.30
0.4	circle	all	4088	0.24 ± 1.10	0.49 ± 0.64	0.18 ± 1.01	0.38 ± 0.39
0.8	circle	all	2006	-0.59 ± 1.17	0.13 ± 0.57	-0.86 ± 1.11	-0.06 ± 0.29
0.2	triangle	all	2673	0.99 ± 1.00	0.86 ± 0.51	1.44 ± 1.43	0.71 ± 0.89
0.4	triangle	all	2030	0.70 ± 1.00	0.90 ± 0.55	0.87 ± 1.20	0.93 ± 0.37
0.8	triangle	all	1505	0.36 ± 1.34	0.66 ± 0.61	0.27 ± 1.49	0.90 ± 1.14
all	all	0.00	2875	1.33 ± 1.07	0.67 ± 0.60	1.17 ± 1.62	0.61 ± 0.95
all	all	0.05	3221	0.51 ± 1.14	0.62 ± 0.55	0.59 ± 1.35	0.42 ± 0.65
all	all	0.10	3289	0.15 ± 1.11	0.48 ± 0.54	0.15 ± 1.24	0.59 ± 0.85
all	all	0.15	3228	0.20 ± 0.93	0.42 ± 0.54	0.09 ± 1.13	0.37 ± 0.50
all	all	0.20	3453	0.01 ± 1.07	0.52 ± 0.71	-0.04 ± 1.26	0.50 ± 0.73

Table 8.5 gives the percentages of droplets that were deposited on, off, or partial on the target. In addition, the two size factors are given: the ‘processing detection size factor’ and the ‘spray cells area size factor’. For all the targets combined, 92.9% of the droplets was deposited on-target, 4.5% was off-target and 2.6% was partial on-target. The droplets that were deposited off-target were always close –within 2 cm – to the target, as can be derived from the longitudinal and transversal deviations shown in Table 8.4. The percentage on-target droplets was higher for the circles compared to the triangles. No relation was found between the height of the target and the percentage of on-target droplets. A relation between the height of the target and the size factors was found. An increasing target height, which means that the object is closer to the camera, results in a larger size factor. For instance an object on the soil surface had a processing size factor of 1.04 whereas an object at 20 cm height had a processing size factor of 1.25. The same holds for the spray cells size factor, with a value of 0.77 and 0.95 for 0 cm and 20 cm respectively. So, taller objects had an overestimated area between 4 and 25 % within the processing algorithm. This could have caused droplets falling outside the target.

However, this did not happen as droplets were only placed on each 1x4 cm area. In summary, on higher targets the droplets were positioned closer to the boundaries of the targets, but they were not incorrectly deposited outside the borders of the targets.

Table 8.5 Percentage of droplets on, off, or partial on target deposited and size factors of the processed targets compared to the size of the scanned result image. The values are presented for the different shapes, velocities and heights during the precision evaluation experiment.

Velocity, m s^{-1}	Target shape	Height, m	% on targets	% off targets	% partial on target	Processing size factor	Spray cells size factor
all	all	all	92.9	4.5	2.6	1.15	0.88
all	circle	all	95	2.9	2.2	1.15	0.91
all	triangle	all	89.5	7.2	3.3	1.15	0.84
0.2	circle	all	95.5	2.1	2.3	1.14	0.92
0.4	circle	all	94.2	3.3	2.4	1.15	0.94
0.8	circle	all	95.4	3.3	1.3	1.16	0.87
0.2	triangle	all	89.4	7	3.6	1.15	0.83
0.4	triangle	all	89.1	7.7	3.2	1.17	0.9
0.8	triangle	all	91	6.6	2.9	1.15	0.81
all	all	0.00	90.4	6.7	2.9	1.04	0.77
all	all	0.05	94.2	3.6	2.3	1.1	0.86
all	all	0.10	93.7	3.8	2.5	1.15	0.88
all	all	0.15	93.5	3.8	2.7	1.22	0.93
all	all	0.20	92.3	5	2.7	1.25	0.95

8.5 General discussion

Comparison of the system with the program of requirements as given in Table 8.1. Req. 2) was in our research achieved through covering the camera field of view and using xenon work lamps. From literature (Steward & Tian, 1998; Marchant & Onyango, 2001) it is known that algorithms can also handle daylight changes, but this would result in a computational burden on the real-time system. Req. 8) was achieved at 20 cm working width. Five micro-sprayer needles were spaced 4 cm apart. Adding more micro-sprayer valves and needles could extend the working width easily. Req. 1), the vision detection has a spatial resolution of 1 pixel mm^{-1} for vegetation detection. Although, in the image processing steps the vegetation grid cells have a size of 1 cm^2. So, resolution decreases when processing vegetation grid cells. As a consequence this fits to the Req. 3) as the detection system supplies information each cm^2. However, the micro-sprayer needles are spaced 4 cm apart and this mechanical limitation reduces resolution in transversal direction with a factor 4. This did not hamper the quality of application, as the minimum plant size on which glyphosate was applied was 12 cm^2. Req. 4) is realized with the micro-sprayer that applies a gel fluid. The droplets had a size of 20±5 μL and were deposited well on target without splash. Although, during droplet formation in the air, some satellite droplets are formed. These satellite droplets might cause crop damage. The risk of these droplets was not specifically investigated, but their effect was included in the percentage of controlled sugar beet plants in this research, as it was a true field test. Req. 5) could not be reached in our research. Up to 1 m s^{-1} travel velocity was possible with the detection system. Most important was that the maximum droplet generation frequency was 80 Hz, which limited driving speed to 0.8 m s^{-1}. Req. 6) and 7): Volunteer plants were controlled up to 82.8 and 71.2 % at sand and clay soil respectively. Sugar beet plants were controlled 1.4 and 0.6 %. A higher percentage of control of volunteer plants is required. Given the current system software and hardware a higher percentage of control of volunteer potato plants can be achieved but this is at the price of a higher percentage of control of sugar beets.

From the results several error sources were identified. For example the height measurements and the microsprayer droplet velocity. The droplet velocity could not be measured real-time during the experiments. However, the droplet velocity has a large influence on the deviations in droplet positioning in longitudinal direction. This can be derived from Equation 8.1, a standard deviation on the droplet velocity $\boldsymbol{v_{zd}}$ of 0.2 m s^{-1} gives for a travel velocity $\boldsymbol{v_{xp}}$ of 0.4 m s^{-1} and a distance $\boldsymbol{d_z}$ of 30 cm a range on $\boldsymbol{d_x}$ of 1.2 cm. In general all the standard deviations that were shown in Table 8.4 can be explained by fluctuations in droplet velocity in $\boldsymbol{v_{zd}}$. A system where droplet velocity can be measured, or even better, can be controlled, will enhance the accuracy of droplet positioning.

The proof of principle machine in our research had a working width of 1.5 m and a max travel velocity of 0.8 m s^{-1}. This would result in approximately 2.5 hrs work load for control of 1 ha. Compared to the actual labour requirements up to 20 hrs ha^{-1} this is a reduction in work load by an order of magnitude when an automated system is used.

Compared to the system of Sogaard and Lund (2007) their spray cell size had an area of 25 mm^2, our system has a spray cell size of 400 mm^2. This means our system is a factor 16 coarse compared to their micro-spray system. However, when the number of needles in our system is increased to 1 per cm in transversal direction, the spray cell size becomes 100 mm^2. This increases resolution and fits to the detection algorithm.

Compared to Sogaard and Lund (2007) our experiment was carried out under natural field conditions. This is an advantage over the indoor conditions that were used in their research. The system in our research could continuously travel and process images and spray. This is an advance and brings the technology closer to practical application in field conditions. This experiment was conducted in autumn, which did not represent growth stages from regular springs. We expect that the results will be comparable to spring conditions as the system adapted to the actual plant colors that were present in the field. Although, further experiments have to support the results, so that percentages control of plants can be generalized to other field situations.

Our system used a systemic herbicide that required precise application without drift. Extension to non-systemic crop protection chemicals that require a larger coverage of the crop can now be made. This would save large amounts of crop protection chemicals in early growth stages as proposed with canopy density spraying (Zande & Achten, 2005). An outlook for future use of the system would be that besides weed control, the system shows potential for plant specific nutrient application – on the plant or close to the plant – and plant specific crop protection chemical application.

8.6 Conclusion

Quantification of the performance of the proof of principle machine in field conditions was the objective. A first experiment demonstrated that in field conditions volunteer plants were controlled. Within the seed line, glyphosate was applied on weed potato plants with up to 100% controlled plants at 0.2 m s^{-1} and between 75% and 83% control at 0.8 m s^{-1}. This was accompanied with up to 1.4% unwanted control of sugar beet plants. A second experiment demonstrated that the accuracy of the micro-sprayer targeted droplets was ±1.4 cm in longitudinal direction and ±0.75 cm in transversal direction. This accuracy was sufficient as the minimal sprayed plant size was 12 cm^2. Finally, the proof of principle machine had an approximated capacity of 2.5 hrs ha^{-1}, which is on some fields an order of magnitude improvement over current control practices.

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Chapter 9

Discussion, conclusion and outlook

9.1 Discussion

Introduction

In this research, the main objective was “to develop an automated detection and control system for volunteer potato plants in sugar beet fields”. The automated system for volunteer potato detection and control was developed with a systematic design method. In this context, the development led to the following question related to the main objective: What are the requirements for automated detection and control of volunteer potato plants in sugar beet fields? In the introduction of the thesis, these requirements were posed. Then, application of the systematic design method yielded the functions that had to be fulfilled with the system. In the preceding chapters the resulting detection and control system has been described and its quality has been assessed with data gathered in experimental fields. Now, the achieved results are compared with the requirements that were set for the integrated system. Furthermore, the answers to the research questions as given in the individual chapters are joined and connected, to put the achievements of this research into perspective. First, the detection of volunteer potato plants is discussed. Second, the control of volunteer potato plants is considered. Finally, the integral performance of detection and control on the proof of principle machine is discussed.

Detection of the volunteer plants

In Chapter 2 the narrow band reflectance properties of volunteer potato plants and sugar beets were investigated. Both in the range of sensor 1 (450-900 nm) and in the range of sensor 2 (900-1650 nm), combinations of wavelength bands were responsible for discrimination. When the “10 optimal” adapted waveband sets were generalized to a set of “10 fixed” wavebands, the classification results decreased. Then, a further reduction and generalization to “3 fixed” wavebands, resulted in a significantly lower classification performance. These three fixed frequency bands were in the range of sensor 1: 450, 765, and 855 nm and in the range of sensor 2: 900, 1440, and 1530 nm. Classifications were performed with a discriminant analysis, a neural network with one hidden neuron, and a neural network with two hidden neurons. In general, a neural network with two hidden neurons gave the best classification results, followed by discriminant analysis and finally a neural network with one hidden neuron. From this analysis it can be concluded that for best classification results it is required that the wavebands are adapted to the specific field situation. This secures an optimal discrimination between volunteer potato and sugar beet pixel spectra.

Within the visible and within the near-infra red region, wavebands were responsible for discrimination. Therefore, in addition to the 3-CCD color camera that was used in Chapter 3, also a camera sensitive in the near-infrared range was added to measure in the near infrared range. The cameras used in Chapter 5 were sensitive in the range of 400 – 700 nm (RGB) and 700 – 1000 nm (NIR). Broadband color cameras were chosen instead of specific narrow band sensors, because they provide a wider range in which discrimination can be made between volunteer potato and sugar beet . Both cameras together measured four of the most important discriminative wavebands as reported in Chapter 2, actually 450, 765, 855, and 900 nm. These narrow band features were seen in the broadband color features as well in the discriminant analyses from Chapter 4 and 5. In those discriminant analyses Red-Blue which relates to 765 and 450 nm was selected, as well as NIR and NDVI, that relate to 900, 855, and 765 nm. The required detection accuracy and precision of 4 mm^2 as defined in Chapter 1 was realized with the camera detection system. Specifically, the cameras had an image sensor of 1628×1236 pixels. In the measurement setup, images were grabbed of 1628×198 pixels that corresponded to 1.50×0.18 m. So, this corresponded to a spatial resolution of 1.1 pixel per mm.

Natural light conditions influence the classification results when machine vision is used (Marchant *et al.*, 2001). As a consequence, the pixel classification results ranged between 49 and 97% with a static Bayes classifier and a static neural network (Chapter 3). However, adaptive classification, taking into account the changing natural light conditions, increased classification accuracy from 34.9 to 67.7% (Chapter 4). This was proven as adaptive and non-adaptive (static) classification was applied under changing and constant natural light conditions.

Though, under constant natural light conditions adaptive classification was better than a constant classifier, as classification accuracy increased from 84.6 to 89.9% (Chapter 4). Under constant light conditions, either natural or in controlled environment, an adaptive classifier taking into account the crop growth stage, and the local crop and volunteer potato color and texture features outperforms a static classifier. This agrees with Chapter 2 – controlled conditions – , where for spectral reflectance measurements the same was stated for adaptive classification, the performance was better when the classifier was adapted to the local crop and weed properties. On one hand, adaptive classification was required because the natural light conditions changed during operation, on the other hand, the crops and weeds varied over the field. The first issue of changing natural light conditions was tackled by creating a controlled environment, with constant light conditions (Chapter 5). The second issue of varying properties of crops and weeds cannot be taken away. Therefore, adaptive algorithms as applied in this research have to cope with these varying crop and weed properties within the field.

In Chapter 2 and 3 neural networks and statistical methods were used for classification of multivariate feature vectors of sugar beet and volunteer potato plants. Though neural networks outperformed Bayesian classifiers in classification performance as shown in Chapters 2 and 3, Bayesian algorithms are preferred for real-time classification for the following reasons. First, the calculation time is independent from randomization steps within the calculation. Second, there is no risk of getting stuck in a local minimum instead of a global minimum during training of the classifier. Furthermore, on-line learning of neural networks is computationally intensive. So, the Bayes classifier was used despite the ability of the neural networks to model nonlinear classification rules. However, in future classification systems, kernel density estimation (Bishop, 2006) could be introduced to better estimate the probability density distribution of the feature values to optimize the solution of the Bayes classifier as well. Furthermore, adaptive feature selection (Roth & Lange, 2004; Agrawal & Bala, 2008) might be introduced to reduce the calculation load in a real-time system, because we discovered in Chapter 4 and 5 that of ten features used, only three to six were actually significantly contributing to the classification. However, these features were not always the same, supporting an adaptive feature selection system.

Stated in Chapter 1, the control percentage for volunteer potato plants was 95% and for sugar beet a maximum of 5% was listed in the program of requirements. In Chapter 8 was concluded that 83% of volunteer plants was controlled with unwanted control of sugar beet plants of 1.4%. There is a trade-off between unwanted control of sugar beet plants and the percentage control of volunteer potato plants. When more control of sugar beets is allowed, a higher percentage of volunteer potato plants will be controlled as well. This is caused by a change in the decision boundary within the Bayes classifier, for example by adjusting the a priori chances as explained in Chapter 5

Control of the volunteer plants

The micro-sprayer used gel instead of water to apply glyphosate on the volunteer potato plants. As this was an innovative and new method, the efficacy of flat fan applied glyphosate in water (Chapter 6) was compared with flat fan applied glyphosate in gel (Chapter 7). As glyphosate in gel gave equivalent efficacy on the volunteer potato plants compared to glyphosate in water, glyphosate was also applied in gel with the micro-sprayer. With the micro-sprayer individual droplets could be deposited on demand, and different droplet densities were sprayed. Leaf dry weight and photosynthesis activity showed that low density distribution patterns performed worse than high density micro-sprayer droplet distributions.

The micro-sprayer realized the required deposition patterns for volunteer potato control. This means that a sufficient amount of glyphosate could be deposited to achieve full control of shoots and tubers according to the requirements in Chapter 1. In Chapter 6 the dose required for effective control of volunteer potato plants ED_{90} was estimated at 843 μg a.e. glyphosate per plant. This was preferably applied on plants of a small growth stage with an area of 53.3 cm^2. In Chapter 7 the high density distribution of 3022 droplets m^{-2} with 3.30 mg $droplet^{-1}$ has shown the best efficacy for both photosynthesis activity as well as for control of the total leaf dry weight. The micro-sprayer droplet density × potato plant area × mean mass of single droplet yields 52.8 mg gel per plant that has to contain at least 843 μg a.e. to be 90% effective for control of tubers and shoots. This is a 2% glyphosate solution in the gel, which agrees with the conclusions from both Chapter 6 and 7.

Weed potato plants always grow within and between crop plants. Therefore, the tolerance of the crop to the herbicide application on the weeds is important as well. Although, in our study the application of glyphosate on sugar beet plants was prevented as much as possible, further experiments are required to determine the tolerance of sugar beet to glyphosate. Within the micro-sprayer dose-response experiment, limited data of greenhouse grown potato plants was available. This prevented a broad generalization of the dose effect study of the micro-sprayer. More field experiments with the micro-sprayer should support the findings from the greenhouse grown volunteer potato plants dose-effect study, and could determine the tolerance of sugar beet plants against small amounts of glyphosate.

Integrated system performance

The system had a working width of 1.5 m and this was also the width of the field of view of the cameras. Both physically and for the resolution this was a maximum distance for the following reasons. An angle of view of 45 degrees from the lens determined that the camera had to be positioned 1.5 m above soil level. A higher mounting of the camera would have increased working width. But this would have resulted in a lower resolution as a larger area was then imaged on the same amount of pixels. Sugar beets are seeded with 0.5 m between the seed lines, thus three rows of sugar beets fitted in the system used in this research. So, the detection system fulfilled the requirement of modularity for three rows of sugar beet plants. For one sugar beet row a micro-sprayer was developed with a working width of 0.2 m. The complete system was attached to the tractor hitch and was leveled with continuously variable supporting wheels. Because of the controlled light conditions in the system, created by a hard cover and additional lighting, the rigid frame could in future easily support band sprayers to treat the area between the sugar beet crop rows, that is until now not treated with the current system.

Within the image processing steps, data of 11×11 pixels was binned to one grid cell, on one hand to provide the correct resolution for the actuator at 10×10 mm, and on the other hand to reduce calculation time within the real time algorithm. This resulted in a reduction from 322344 pixels to 2664 grid cells that needed computation, which was a factor 11^2=121 reduction in calculation load. The resolution was retained at 10×10 mm or 100 mm^2 and requirement as listed in the program of requirements was met. This approach was similar to Evert *et al.* (2008). They processed tiles of images to increase processing speed of their algorithm. For the actual control action, a micro-sprayer was used that had five needles spaced 0.04 m apart, yielding a total working width of 0.20 m. This meant that a resolution of 0.01 m perpendicular to the driving direction could not be realized. As discussed before, 3022 droplet m^{-2} are required to achieve optimal control, though in the current configuration up to

2500 droplets m^{-2} can be deposited. Along the driving direction, the valves could be individually activated with a maximum of 80 Hz, which means that up to 0.8 m s^{-1} the resolution was at minimum one droplet per 0.01m in travel direction. Though, to achieve a high efficacy in the field, the glyphosate concentration was raised from 2% to 5% in the evaluation experiment in Chapter 8 for the following reasons: 1) The realized droplet density was lower compared to the optimal density from Chapter 7. 2) Plants were not exactly lined up in the seed line as they were in the dose response experiment; 3) ED_{90} does not guarantee a maximum performance in the field. Within the seed line, weed potato plants were micro-sprayed with the 5% solution in gel, resulting in up to 100% controlled plants at 0.2 m s^{-1} and between 75% and 83% controlled plants at 0.8 m s^{-1}. This was accompanied with up to 1.4% unwanted controlled sugar beet plants.

A second experiment demonstrated that the accuracy of the micro-sprayer targeted droplets was ±1.4 cm in longitudinal direction and ±0.75 cm in transversal direction. In the program of requirements from Chapter 1, the requirement was set at 100 mm^2 control resolution. The realized precision was at 14 mm ×7.5 mm yields 105 mm^2. Though, this was not a square, but rectangle shaped precision. However, this accuracy was sufficient as the minimal sprayed plant size was 12 cm^2. Finally, the proof of principle machine had an approximated capacity of 2.5 hrs ha^{-1}, which is on some fields an order of magnitude improvement over current control practices with band sprayers (Womac *et al.*, 2004) and manual application with a selector (Mangnus, 2005). Yet, it does not meet the requirement of travel speed as stipulated by a driving speed of 2 m s^{-1}.

Adaptive classification algorithms were required as was concluded from Chapter 2, 3, and 4. Therefore, in Chapter 5 the crop row position and crop row width were determined and a Kalman filter improved tracking of the rows, to adapt to the varying properties of the crop in the field. This resulted in good quality training data for the Bayes classifier. In one of the fields, 96.6% volunteer potato classification and 8.0% sugar beet misclassification was achieved. The classifier was designed as an unsupervised system and featured automatic training. The only a priori data that was required, was the distance of 0.5 m between the crop seed lines. The training phase consisted of filling of the vegetation grid cell buffers of 500 cm^2 as explained in Chapter 4 and 5. Depending on the number and growth stage of the sugar beet and volunteer potato plants in the field it takes between one and approximately twenty images, between 0.2 and 4 m before the classifier is trained and can actually discriminate between sugar beet and volunteer potato plants.

Real time systems have to be programmed deterministically to maintain their real time behavior. Although, for a measurement and control system within a natural environment, it is hard to determine what will happen in future time steps. Notwithstanding the unpredictable environment, our system proved to work robustly. This was realized through a worst case scenario of 75% vegetation within an image that had to be processed within the time budget of the real-time computing system. The 195 ms loop time for processing an image of 0.2 m length could be realized within a worst case of 75% green vegetation within an image. When an image contains between 75 and 100% vegetation, the travel speed has to be reduced as all vegetation has to be processed before spraying can be activated. In this case, a warning could be given as part of the feedback system. To solve this drawback, fortunately newer real-time computers already have four instead of one processor core for computation. This provides for faster calculation to increase travel speed or to increase detection resolution and working width. Furthermore, faster valves and insight in droplet formation are required to maintain the droplet distribution pattern of 3022 droplets m^2 at higher travel velocities.

In both Chapters 5 and 8 feedback mechanisms were shortly proposed for the detection and control system. The main reason was that the application of glyphosate can damage a complete crop when the system behaves imperfect. Since a driver is not able to exactly monitor the performance due to the driving speed and the high precision of application, indicators of performance as well as robust operation are required. Since they are crucial parts of this system, monitoring and feedback control should be implemented on the lighting, row detection, number of plants detected, the amount of spray fluid used, and blockages in needles. Also external factors like terrain roughness and wind and vibration should not be neglected in the further development of the system. Until now, the system has been tested while driving over a smooth surface at a speed of 0.8 m s^{-1}. Under these conditions the system performed well. Monitoring of performance was implemented on the classification results. This was done with the Fréchet distance measure between multivariate distributions that gave an indication of the expected classification performance. The distance measure was significantly ($P<0.05$) smaller when the classification results were of poor quality (Chapter 5). In this way, the expected performance was part of the unsupervised classification system. Using such a quality indicator, the application of glyphosate -with an actuator- can be halted in fields where classification is problematic, to minimize crop damage and economic losses.

Ground truth images were used to determine the actual accuracy and number of plants that were classified. It is important to validate the results of algorithms on data that provide for generalization of the results to other situations (Thacker *et al.*, 2008). In this research, the detection algorithm results were validated in two seasons on two fields that provided sufficient information and ground truth data. Creating ground truth data was a tedious job, but has to be done carefully. Even humans make mistakes when classifying plants behind a computer. Therefore, personal experience in this research showed that evaluation of ground truth from multiple persons is required, result in reliable data.

With the micro-sprayer, the required number of plants could be controlled in field experiments. However, to reach the required 95% control of volunteer plants, a cascade of elements has to work correctly within the system. First, enough vegetation grid cells within one potato plant need to be classified as volunteer potato plant as the detection system is based on cm^2 precision and not on complete plants within the algorithm. Therefore, the real percentage of controlled plants can only be determined afterwards, and not during operation in the field. Then, valves on the microsprayer were activated when 3 out of 4 cm^2 was classified as volunteer potato, to minimize the sugar beet damage. Evaluation afterwards based on ground truth, resulted in between 90.8 and 96.6% of volunteer potato plants that were detected with 8.0 and 7.4% misclassified sugar beet plants in May and June 2008 (Chapter 5). In the experiment of October 2008 the results were between 75 and 83% detected volunteer potato plants with up to 1% misclassified sugar beet plants (Chapter 8). Finally, within the field experiments in October 2008 between 71.2% and 82.8% was controlled with undesired control of sugar beet plants up to 1.4% (Chapter 8).

Undesired control of sugar beet plants could become higher for two reasons. The sugar beet plants were false negative classified, or the plants incorrectly received a droplet of glyphosate. False negative sugar beet classification occurred in all the experiments we performed. This is caused by the natural appearance of the colors of the plants. Especially in larger sugar beet growth stages, sugar beet plants become darker green and look more similar to volunteer potato plants. Though, it is possible to better adapt to these growth stage specific appearance. Due to the random nature of the appearance of volunteer potato plants in sugar beet fields, it should be possible to improve the classification scheme. This can be accomplished by keeping track of the amount of vegetation that is found between the crop rows that have to be weeds, together with the amount of volunteer potato plants that is classified within the crop rows. When these numbers do not match with each other or differ too much, the a priori chances within the Bayes classifier require modification.

Incorrectly positioned droplets could also cause undesired control of sugar beets. In Chapter 8 we showed that droplets could be deposited with an accuracy of ±1.4 cm in longitudinal direction and ±0.75 cm in transversal direction. When droplets are deposited, a margin has to be kept along the edges of the plants because that secures correct deposition of droplets. Besides accurate position, research revealed that during the descent of a droplet from the micro-sprayer to the volunteer potato plant, satellite droplets are formed. These small droplets of approximately 0.1 μL could probably have killed some sugar beet plants as well. Although, the harmful effects of satellite droplets are still unknown. The fluid, needle and pressure properties could be optimized to further reduce the formation of these satellite droplets.

9.2 Conclusion

In the introduction in Chapter 1, seven research questions were posed. They were answered in the individual chapters, and the answers were joined and related to each other in the discussion section. The questions were:

1) What reflectance properties can be used for detection of volunteer potato plants?
2) What are best suited methods to classify image pixels?
3) What is the improvement of á priori information in an adaptive classification algorithm?
4) How to implement the algorithms in a real-time system?
5) What is the dose-response of tuber yield and photosynthesis activity of volunteer potato plants to glyphosate?
6) What are the perspectives in using a micro-sprayer for volunteer potato control?
7) What is the integrated system performance?

The answers to the seven research questions can be grouped together as: 1) detection of volunteer potato plants; 2) control of volunteer potato plants; and 3) real time implementation of detection and control on a proof of principle machine.

1) Detection of volunteer potato plants

A real-time unsupervised adaptive Bayesian classifier is required to discriminate volunteer potato plants from sugar beet plants in machine vision images. Both a red, green, blue color camera and a near-infrared camera are required as wavebands in both ranges represent discriminating wavebands. Especially, adaptive algorithms are required and give significantly better results when volunteer potatoes between sugar beets need to be detected in arable fields, as the properties of crops and volunteer plants change within the field. Application of the algorithm led to 97% classification of volunteer potato plants in experimental fields.

2) Control of volunteer potato plants

The micro-sprayer configuration where droplets of 3.3 μL are deposited every 1×4 cm length×width is sufficient to apply a lethal dose of glyphosate to the volunteer potato plants; the tuber and shoots are fully controlled. This micro-sprayer controls the volunteer potato plants with less glyphosate compared to flat fan nozzles. For the plant sizes sprayed in the micro-sprayer dose-effect study, the herbicide savings of a micro-sprayer compared to an on-off switching flat fan nozzle range between 27 and 95%.

3) Real time implementation of detection and control on a proof of principle machine

Within this research a proof of principle machine for automated detection and control of volunteer potato plants in sugar beet fields has successfully been developed. The system performs closely to the requirements that were set in advance of the research. The cycle time is 195 ms per image of 20 cm length, this together with the maximum operation frequency of the micro-sprayer of 80 Hz, results in a travel speed of 0.8 m s^{-1}. Performance feedback mechanisms are required for robust real-time operation. A feedback parameter on the expected classification performance is implemented to prevent damage on the crop plants. The approximated capacity of the proof of principle machine is 2.5 hrs ha^{-1}. Up to 83% of the volunteer plants were controlled with 1.4% unwanted controlled sugar beet plants.

To sum up, within this research a proof of principle machine for automated detection and control of volunteer potato plants in sugar beet fields has successfully been developed. The system performed closely to the requirements that were set in the start-up of the project. So, the system is an example of new technology that can be applied to practical applications to reduce the amount of required labor and to reduce the crop protection inputs for weed control in arable farming.

9.3 Outlook

The system is an example of new technology that can be developed for practical applications to reduce the amount of required labor and to reduce the crop protection inputs in arable farming. Utilization of the technology was one of the supporting factors during the development of the system. On several field demonstration days the developed system was shown to end-users. This motivated the author to continue the research and the end-users were enthusiastic on the progress of automated detection and control techniques. End-users like the precise detection and control system because it applies crop protection chemicals where they are required, on the plants and not on the soil, as far as it concerns weed control. However, the market opportunities are relatively small for volunteer potato control only, it is a niche market machine. But the end users indicated they would like to use the system for other purposes as well, which might be possible after further research and product development. Some examples of future use are: 1) volunteer potato control in other row crops like onions, carrots, and chicory, 2) control of other problem weeds in row crops. Not only crop protection chemicals can be used in the system, also nutrients can be applied more precise to plants. At higher pressures, nutrients can even be injected in ‘close to crop’ regions. It would even be possible to change the substance of the gel in a way that it releases the chemical slowly to the crop plants. When the resolution of the system is increased, even weed seedlings could be targeted as shown in experimental fields already (Giles *et al.*, 2004; Sogaard & Lund, 2007). The proof of principle machine in this thesis showed improvements in both travel speed and capacity in experimental fields.

Besides research to broaden the application scope of the machine, it is good to notice that new precision application technologies like micro-sprayers for crop protection application require new dose effect studies as well. Not all crop protection chemicals can be simply applied by using a micro-sprayer droplet distribution with the same efficacy as flat fan nozzles. Modes of action of the crop protection chemical have to be taken into account. Also, further developments will have to reduce the formation of satellite droplets from the micro-sprayer.

This can be done by adjusting the properties of the gel, and by adjusting the pressure and needle orifices. A method to adjust the fluid has been presented by Downey *et al.* (2004)

In future, these precision detection and application systems do not have to work behind a tractor but can work attached to autonomous vehicles. Not economy of scale but economy of quality will determine the success of precision detection and application technology in arable farming.

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Summary

High amounts of manual labor are needed to control volunteer potato plants in arable fields. Due to the high costs, this leads to incomplete control of these weed plants, and they spread diseases like ***Phytophthora infestans*** to other fields. This results in higher environmental loads by curative spraying of crop protection chemicals, which is in contradiction to the required decreased use of crop protection chemicals to save the environment. Therefore, the main objective of this thesis was "to develop a system for automated detection and control of volunteer potato plants". A systematic design approach was used to define a program of requirements and to identify and order possible solutions to accomplish the detection and control. The main requirements were a travel speed of up to 2 m s^{-1}, resolution of control at least 10×10 mm, work under variable natural light conditions, control of volunteer plants > 95%, and undesired control of sugar beet plants < 5%. The design strategy resulted in color and near-infrared machine vision as detection method and a micro-sprayer for application of glyphosate as a result. Furthermore, issues were identified that required further investigation to successfully come to a proof of principle machine. The research was then focused on:

- Detection of volunteer potato plants,
- Control of volunteer potato plants,
- Real-time implementation of integrated detection and control on a proof of principle machine.

For the purpose of detection of volunteer potato plants, the narrow band spectral reflectance properties of volunteer potato plants and sugar beet plants were analyzed. Narrow band spectral measurements were done in 2006 and 2007 on two different fields. This resulted in 15 datasets on clay and sand soil. Discriminating wavebands were selected and classified with neural networks and statistical discriminant analysis. A neural network with two hidden neurons performed best for classification. Two sensors were used covering the range from 450 to 900 nm and from 900 to 1650 nm. Both visible and near infra-red wavebands were responsible for discrimination. From the analysis 450, 765, and 855 nm from sensor 1 and 900, 1440, and 1530 nm from sensor 2 were identified as important discriminative wavebands. However, the discriminative wavelengths depended on field and crop status and could not be generalized. Ten wavebands that were optimally adapted to the datasets gave 99% true negative classification of volunteer potato plants. On the other hand, a fixed set of three wavebands that was not adapted to the individual datasets gave 80% true negative classification of volunteer potato plants. This indicates that adaptive feature sets are required for classification.

The development of the machine vision detection system started with measurements in 2005. Color based detection showed that the difference in classification results was larger between fields than the difference between a static neural network and static Bayesian classification.

Then, machine vision measurements in 2006 with a color camera under changing and constant natural light conditions showed that crop and weed properties change within a field. An adaptive instead of static classification increased classification accuracy from 34.9% to 67.7% under changing light conditions. Under constant natural light conditions, the classification accuracy increased from 84.6% to 89.8%. So, adaptive classifiers are required and were implemented in the further research as these gave significantly higher classification results. As a next step, besides a color camera also a near-infrared camera was used for imaging within the proof of principle machine, as this gave a better feature set for classification. Additionally, the field of view of the cameras was shielded and artificial light was used to maintain constant light conditions. For the real-time implementation, an unsupervised adaptive Bayesian classifier was used. The crop row position and crop row width were determined and a Kalman filter improved tracking of the rows, to adapt to the varying properties of the crop in the field. Data from between the crop rows was trained as the volunteer potato class and data from within the crop row was trained as the sugar beet class. This resulted in good quality training data for the Bayes classifier. The system was unsupervised, as it learned and trained itself based on row recognition. The features that were used for training and classification were: blue, hue, saturation, excessive green, red minus blue, near-infrared and near-infrared difference vegetation index (NDVI). These feature values within the training data were continuously locally adapted, in two first-in-first-out buffers both with an area of 500 cm^2 for sugar beet and volunteer potato plants. Measurements were done on seven days in 2007 and 2008. The results showed a trade-off between the percentage of correct classified volunteer potato plants and the percentage of misclassification of sugar beet plants. In one of the fields 96.6% volunteer potato classification and 8.0% sugar beet misclassification was achieved.

Connected to the detection system was a micro-sprayer that applied glyphosate in gel to the volunteer potato plants. Spraying gel through a micro-sprayer was innovative. This proved to work in the application of glyphosate on plants. As knowledge of the dose response of glyphosate on potato was outdated and could not be used for plant specific application, a dose-response study was done with flat fan nozzles on 120 potato plants to determine the efficacy of glyphosate. The effect parameters tuber weight and photosynthesis activity were analyzed with log-logistic nonlinear regression methods. This resulted in an amount of 843 μg a.e. per plant for reduction of tuber weight and photosynthesis with 90%. This amount was applied on plants with a height of 6.1±1.39 cm and an area of 53.3±19.6 cm^2. As glyphosate was to be applied with a micro-sprayer, the dose-response study was extended to 500 greenhouse grown potato plants. Five application methods were used: 1) flat fan water application, 2) flat fan gel application, 3) micro-sprayer low density distribution, 4) micro-sprayer medium density distribution, and 5) micro-sprayer high density distribution. As effect parameters again tuber weight, photosynthesis activity, and in addition shoot dry weight were used. They were analyzed with ANOVAs and box-plots. The micro-sprayer dense distribution with 3022 droplets m^{-2} and 3.3 mg per droplet had the best efficacy. The micro-sprayer controlled the volunteer potato plants with less glyphosate compared to flat fan nozzles. Furthermore, it had a centimeter precision resolution and low risks of unwanted crop damage.

With real-time hardware, machine vision detection and micro-sprayer were integrated to a proof of principle machine. A travel speed of 0.8 m s^{-1} was reached with the proof of principle machine and it had an approximated capacity of 2.5 hrs ha^{-1}. This was the maximum that could be realized as the micro-sprayer valve actuation frequency was maximally 80 Hz. The image processing time for one image of 0.2 m length was 195 ms. At this travel speed automated feedback systems on the operation of the system are required to support and replace human surveillance. Therefore, the Fréchet distance measure between multivariate distributions was introduced as quality indicator of classification performance. The Fréchet distance measure was significantly smaller when the classification performance was low, as identified on ground truth determined classification results afterwards. This proves that the performance could be predicted with a distance measure between multivariate distributions. In case of poor predicted classification performance, the application of glyphosate with the micro-sprayer can be halted to prevent unwanted crop damage and economic losses. The accuracy of application was ±1.4 cm in longitudinal direction and ±0.75 cm in transversal direction. During a field trial, up to 84% of the volunteer plants were controlled with 1.4% unwanted controlled sugar beet plants.

To sum up, within this research a proof of principle machine for automated detection and control of volunteer potato plants in sugar beet fields has successfully been developed. The system performed closely to the requirements that were set in the start-up of the project. The percentage of 95% controlled volunteer potato plants can be reached. On the other hand, the travel speed still has to be increased from 0.8 m s^{-1} to 2.0 m s^{-1}. The system is an example of new technology that can be developed for practical applications to reduce the amount of required labor and to reduce the crop protection inputs for weed control in arable farming.

Samenvatting

Voor de handmatige bestrijding van aardappelopslag in akkerbouwpercelen is veel arbeid nodig. Vanwege de hoge kosten leidt dit tot een onvolledige bestrijding en worden ziekten als ***Phytophthora infestans*** verspreid naar andere percelen. Dit leidt tot een hogere milieubelasting omdat dan meer en vaker curatieve gewasbescherming nodig is vanwege de hogere ziektedruk. Dit staat haaks op de milieudoelstelling, die juist een reductie in het gebruik van gewasbeschermingsmiddelen beoogt. De doelstelling van dit onderzoek was: "Ontwikkeling van een systeem voor automatisch herkennen en bestrijden van aardappelopslagplanten". Een systematische ontwerpbenadering is gebruikt om een programma van eisen op te stellen en mogelijke oplossingen voor de herkenning en bestrijding te ordenen. De belangrijkste eisen waren een rijsnelheid van 2 m s^{-1}, resolutie van bestrijding 10×10 mm, onder variabele lichtomstandigheden kunnen werken, bestrijding van aardappelopslag > 95%, en ongewenste bestrijding van suikerbieten < 5%. De ontwerpstrategie resulteerde in kleuren- en nabij-infraroodbeeldherkenning als detectiemethode en een micro-spuit voor toediening van glyfosaat. Verder werden verschillende problemen geïdentificeerd welke verder onderzocht moesten worden om een succesvolle testmachine te maken. Het onderzoek richtte zich vervolgens op:

- Detectie van aardappelopslag,
- Bestrijding van aardappelopslag,
- Real-time implementatie van herkenning en bestrijding geïntegreerd om een testmachine.

Ten behoeve van de detectie van aardappelopslag zijn spectrale reflectie-eigenschappen in smalle golflengtebanden van suikerbieten en aardappelopslag geanalyseerd. In 2006 en 2007 zijn op twee verschillende percelen spectrale metingen uitgevoerd. Dit leidde tot 15 datasets op klei- en zandgrond. Onderscheidende golflengten zijn geselecteerd en geclassificeerd met neurale netwerken en statistische discriminant analyse. Een neuraal netwerk met twee verborgen neuronen gaf de beste classificatie. Twee sensoren maten in het golflengtebereik van 450 tot 900 nm en 900 tot 1650 nm de reflectie-eigenschappen. Zowel in het zichtbare, als ook in het nabij-infrarode gedeelte van het spectrum waren golflengtebanden onderscheidend. Van de eerste sensor waren 450, 765, en 855 nm en van de tweede sensor waren 900, 1440, en 1530 nm geselecteerd als belangrijke onderscheidende golflengten. De onderscheidende golflengten waren steeds verschillend, afhankelijk van het perceel en de toestand van het gewas. Daarom konden geen generieke onderscheidende golflengten worden aangewezen. Wanneer tien onderscheidende golflengten aangepast werden aan de dataset, dan werd 99% van de aardappelopslag geclassificeerd. Echter, een vaste set van drie golflengten die niet aangepast was aan de dataset gaf een classificatie van 80% van aardappelopslag. Wat aangeeft dat adaptieve sets van eigenschappen nodig zijn voor classificatie

In 2005 is gestart met de ontwikkeling van een systeem voor herkenning op basis van beeldverwerking. Veldmetingen werden gedaan en herkenning op basis van kleur toonde aan dat de verschillen in classificatieresultaat groter waren tussen percelen, dan de verschillen tussen een statisch neuraal netwerk en een statische Bayesiaanse classificatie. Beeldherkenning met een kleurencamera onder wisselende daglicht- en constante kunstlichtcondities in 2006 toonde aan dat gewas- en onkruideigenschappen veranderen binnen een perceel. Onder wisselende buitenlichtomstandigheden verbeterde een adaptieve in plaats van een statische classificatie de classificatie nauwkeurigheid van 34.9% naar 67.7%. Bij constante buitenlichtomstandigheden ging de classificatie omhoog van 84.6% naar 89.9%. In het vervolgonderzoek zijn daarom adaptieve classificatie-algoritmen geïmplementeerd want deze gaven systematisch een significant hoger classificatieresultaat. In het vervolg van dit project is naast een kleurencamera ook een nabij-infraroodcamera gebruikt omdat dit een betere en uitgebreidere set van eigenschappen geeft voor de classificatie. Het gezichtsveld van de camera's werd ook afgeschermd tegen buitenlicht. Kunstlicht werd gebruikt als belichting ten behoeve van constante belichting van het oppervlak. Voor de real-time implementatie is een Bayesiaanse classificatie zonder supervisie gebruikt. De gewasrijpositie en -breedte werden vastgesteld en het volgen van de rijen werd verbeterd met een Kalman filter, waardoor beter ingespeeld werd op de wisselende eigenschappen van het gewas in het perceel. Eigenschappen van vegetatie tussen de rijen zijn gebruikt als trainingsdata voor de klasse aardappelopslag en eigenschappen van vegetatie in de gewasrijen zijn gebruikt als trainingsdata voor de klasse suikerbieten. Dit leidde tot goede trainingsdata voor de Bayesiaanse classificatie. Het systeem leerde en trainde zichzelf zonder supervisie, op basis van vegetatie-eigenschappen tussen en in de gewasrij. De eigenschappen voor training en classificatie waren: blauw, kleurschakering, kleurverzadiging, excessief groen, rood min blauw, nabij-inrarood, nabij-infrarood-vegetatie index (NDVI). Deze eigenschappen werden continu lokaal bijgewerkt in twee 'first-in-first-out' buffers, beide 500 cm^2 groot. Eén buffer was voor aardappelopslag vegetatiedata, en één buffer was voor suikerbieten vegetatiedata. In 2007 en 2008 werden op zeven dagen veldmetingen gedaan. De resultaten lieten een wisselwerking zien tussen het percentage correct geclassificeerde aardappelplanten en het percentage fout geclassificeerde suikerbietenplanten. In één van de percelen werd 96.6% aardappelopslag geclassificeerd met een misclassificatie van 8.0% van suikerbieten.

Aan de herkenning werd vervolgens een micro-spuit gekoppeld. Deze bracht glyfosaat in een gel op de aardappelplanten aan. De toediening van glyfosaat in een gel door een micro-spuit is innovatief en was een effectief instrument voor de toediening van glyfosaat. De kennis van de dosis-respons van glyfosaat op aardappelplanten was verouderd. Daarom is een dosis-respons studie uitgevoerd op 120 aardappelplanten om vast te stellen wat de effectiviteit was van glyfosaat toegediend met een spleetdop. De effectparameters knolgewicht en fotosyntheseactiviteit werden geanalyseerd met log-logistische niet-lineaire regressie methoden. Dit leidde tot een hoeveelheid van 843 μg actieve stof per plant voor de vermindering van knolgewicht en fotosyntheseactiviteit met 90%. Deze hoeveelheid was aangebracht op planten met een hoogte van 6.1±1.39cm en een oppervlak van 53.3±19.6 cm^2. Om het effect van de toediening van glyfosaat met een micro-spuit verder te onderzoeken werd de dosis-respons studie uitgebreid met 500 aardappelplanten in een kas. Vijf toedieningsmethoden werden gebruikt: 1) spleetdop toediening met water, 2) spleetdop toediening met gel, 3) micro-spuit met lage dichtheid van gel druppels per m^2, 4) micro-spuit met gemiddelde dichtheid van gel druppels per m^2, 5) micro-spuit met hoge dichtheid van gel druppels per m^2. Als effect parameter werden knolgewicht, fotosyntheseactiviteit en ook loofdrooggewicht gebruikt. Deze werden geanalyseerd met ANOVA's en box-plots. De micro-spuit met fijne verdeling had met 3022 druppels m^{-2} en 3.3 mg per druppel de beste werking. De micro-spuit bestreed de aardappelplanten met minder glyfosaat dan de spleetdop. Aantrekkelijke extra kenmerken van de micro-spuit zijn de centimeter precisie resolutie en de geringe kans op gewasbeschadiging.

Beeldverwerking en micro-spuit zijn met real-time hardware aan elkaar gekoppeld op een testmachine. Een rijsnelheid van 0.8 m s^{-1} werd gehaald met de testmachine, wat neerkomt op een capaciteit van 2.5 uur ha^{-1}. Dit was het maximum wat gehaald kon worden omdat de kleppen van de spuit maximaal met 80 Hz geactiveerd konden worden. De tijd voor de beeldverwerking van één beeld van 0.2 m lengte was 195 ms. Bij deze rijsnelheid zijn automatische terugkoppelingen nodig op de goede werking van het systeem. Daarom werd de Fréchet afstand tussen multivariaat normale verdelingen gebruikt als kwaliteitsindicator van de classificatie. Deze afstandsmaat was significant kleiner als de classificatie slechter was, zoals vastgesteld op basis van de werkelijke classificatie resultaten die achteraf vastgesteld werden. Dit toont aan dat de kwaliteit van de classificatie kon worden vastgesteld met een afstandsmaat tussen multivariate verdelingen. In geval van een verwachte slechte classificatie kan de glyfosaat toediening door de micro-spuit worden gestopt. Dit voorkomt ongewenste gewas- en economische schade. De nauwkeurigheid van de toediening was ±1.4 cm in de rijrichting en ±0.75 cm dwars hierop. Van de aardappelopslag werd 84% bestreden met 1.4% ongewenste bestrijding van suikerbieten planten.

Samengevat, binnen dit onderzoek is een testmachine voor automatisch herkennen en verwijderen van aardappelopslag in suikerbietenpercelen succesvol ontwikkeld. Het systeem voldeed bijna aan het programma van eisen dat aan de start van het project werd opgesteld. Het percentage van 95% bestrijding van aardappelopslag kan worden gehaald, maar de rijsnelheid moet nog omhoog van 0.8 m s^{-1} naar 2.0 m s^{-1}. Het systeem is een voorbeeld van nieuwe technologie die door de praktijk opgepakt kan worden. Het vermindert de arbeidbehoefte en verlaagt de hoeveelheid gewasbeschermingsmiddel die nodig is voor onkruidbestrijding in de landbouw.

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Curriculum Vitae

Ard Nieuwenhuizen was born on September 27th, 1980 in Hoogmade, The Netherlands. After completing high school at Bonaventura College in Leiden, he studied Agricultural Engineering at Wageningen University. During his studies he did an internship for 6 months at the R&D department of Kverneland Taarup, Kerteminde, Denmark, after which he completed his studies with a major thesis in logistics for automated feeding systems on dairy farms and a minor thesis in fertilizer spreading and precision agriculture. After finishing his studies in 2003, there was the opportunity to join the Farm Technology Group in a PhD position. The research concerned the development of a system for automated detection and control of volunteer potato plants and the results are described in this thesis. Since August 2009 Ard Nieuwenhuizen works as a researcher at Plant Research International (WUR) within the team Field Technology Innovations from business unit Agrosystems research.

PE&RC PhD Education Certificate

With the educational activities listed below the PhD candidate has complied with the educational requirements set by the C.T. de Wit Graduate School for Production Ecology and Resource Conservation (PE&RC) which comprises of a minimum total of 32 ECTS (= 22 weeks of activities)

Review of Literature (4.2ECTS)

- Review of literature on automated detection and control of volunteer potato plants (2004)

Writing of Project Proposal (7.1 ECTS)

- Plaatsspecifiek verwijderen aardappelopslag planten (2004)
- Autonoom system voor precisie verwijdering van aardappelopslagplanten (2005)

Laboratory Training and Working Visits (2.8 ECTS)

- Visits to involved companies (2006)
- Detection and precision control of weeds; Aarhus University, Denmark (2008)

Post-Graduate Courses (2.9 ECTS)

- Advanced statistics; PE&RC (2005)
- Multivariate analysis; PE&RC (2006)

Deficiency, Refresh, Brush-up Courses (2 ECTS)

- Basic statistics; PE&RC (2005)
- Supervising MSc theses; WGS (2005)

Competence Strengthening / Skills Courses (7.2 ECTS)
- Scientific publishing (2004)
- Project and time management (2004)
- Personal assessment (2005)
- Academic writing (2006)
- Scientific writing (2006)
- Personal efficacy (2006)
- Career perspectives (2008)

Discussion Groups / Local Seminars and Other Meetings (4.1 ECTS)
- Discussion group meetings Farm Technology Group (2005-2008)
- Crop and weed ecology (2006)

PE&RC Annual Meetings, Seminars and the PE&RC Weekend (1.5 ECTS)
- Introduction weekend (2005)
- PE&RC day (2005, 2006, 2007 and 2008)

International Symposia, Workshops and Conferences (10 ECTS)
- 5 ECPA; Uppsala, Sweden (2005)
- ASAE Annual meeting; Florida, USA (2005)
- 6 ECPA; Skiathos, Greece (2007)
- 5 IWSC; Vancouver, Canada (2008)
- VDI Land. Technik; Stuttgart, Germany (2008)

Courses in Which the PhD Candidate Has Worked as a Teacher
- Field crop technology; Farm Technology Group; 3 days
- Sensor technology; Farm Technology Group; 3 days

Supervision of MSc Students
- Machine vision and microsprayer application of glyphosate on volunteer potato plants; 20 days; 4 students

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