Implementation of a real-time plant detector for a selective grassland weeding machine using high-pressure water jets

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Abstract

The regular forage use of species-rich meadows gets hindered when poisonous plants spread. This can lead to land abandonment, which is critical for the preservation of valuable habitats. Nature conservation regulations prohibit conventional measures, while the alternative of pricking the plants by hand is too labour intensive. A suitable weed control device along with an effective management strategy was developed for this use case, which uses targeted high-pressure water jets to remove harmful plants with small scale treatment. To increase precision and flexibility of the tool a real-time plant detector was employed for the machine control. This paper describes the image analysis method and evaluates the timing of the device control by the visual plant detector. Results of plot trials on repressing *Colchicum autumnale* with the water-hydraulic process and influence of water output and application speed are presented.

1. Introduction

Poisonous plants are unwelcome in grassland populations for forage production. As they spread, the percentage of poisonous plant material in the forage increases and with it the risk of poisoning livestock. Nature conservation regulations limit the range of tools that can be used on extensive areas, which is why the focus is on mechanical solutions to control poisonous plants such as *C. autumnale.* Motivated by the high labour intensity of manual weed control and the widespread loss of fauna when using a mulcher [1] - which conflicts with the aim of nature conservation - a non-chemical site-specific weed control device was developed. This combines nature conservation and the interests of agricultural production.

The weeding device, including an initial control concept, has been described in [2]. A detailed article on an earlier weed detection approach via drone images was published in [3]. While a drone-based weed detection has the advantage of planning routes of the tool in advance to increase the efficiency of the deployment, the new real-time approach makes it possible to locate and treat the target plants more precisely without delay using cameras right in front of the tool. A further reason is to increase practicability and flexibility in use by eliminating the need for surveying the sites with drones prior to the treatment, allowing full machine capacity utilization in the short treatment period in spring.

For the development of the weed detector, images of the target plants were collected and labelled according to [4], from which a convolutional neural network was trained. Furthermore, the prototype device described in [2] was extended to include the real-time detection system the necessary control technology was added and initial camera application software was implemented. The system was developed by Nürtingen-Geislingen University and the University of Ulm and the companies ANEDO, Martin Energietechnik and URACA within a funded project. This paper describes the image analysis method for weed detection and presents its prediction performance. In order to check the correct control, initial tests were carried out on the triggering accuracy of the water jet device with real-time detection. In addition, results from plot trials investigating the weed repression of dynamic waterjet application on *C. autumnale* at different driving speeds and nozzle sizes are laid out.

2. Materials and Methods

For real-time detection of weeds it is crucial to achieve a low inference latency even on constrained hardware. For this reason, we chose an architecture from the EfficientDet convolutional neural network family [6], which was tailored for efficient object detection on mobile devices. For our application, it turned out that model complexity is less important than the input image size. Consequently, the smallest architecture from the family was used (i.e. the EfficientDet-D0) and the image size was set to 768×768 pixel, which turned out to be a good compromise between latency and detection performance. The ground truth dataset was acquired between March 28 and April 20, 2023 using the procedure described in [4] leading to 13656, 6607 and 3129 images for training, validation and testing, respectively. The detection model was trained for 200 epochs. In order to achieve best inference performance, the model was subsequently quantized to 8-bit integers and converted to the tflite file format, which could be integrated into the control system of the treatment tool.

To verify the correctness of the tool control, we conducted a water-jet test. The aim was to study if the theoretically determined parameters, such as machine geometries and offsets between detection and activation of the corresponding nozzles, match the practical application. We used a green coloured wood plank with a size of 0.25 m × 0.1 m as plant dummy, which was detected as a target plant if placed on concrete pavement. The two target variants consisted of either placing one plank lengthwise or orthogonal to the moving direction. Driving speeds were 2, 4 and 6 km/h when moving over the target regulated with the tractors cruise control. The standard rotating nozzle with a working diameter of 0.25 m per section was changed to a point nozzle for better traceability of the water jet. Moreover, we only used the pressure created by the small primer pump to avoid excessive water mist, which would have made the visual evaluation more complicated. Two cameras, one placed right above the nozzle and the other placed on the ground facing the target, were used to determine the activation window of the nozzle. The 0.2 m × 0.1 m size of the paving stones was used as scale when evaluating the videos. Ten replications per speed variant were carried out.

Plot trials were conducted to investigate the effect of the water-hydraulic process on the repression of *C. autumnale*. The control strategy with two treatments and short repetition interval was kept as in [2]. In total 6 replications per variant were made. We introduced the dynamic application of the plots to simulate the tractor-mounted device. Two different nozzle sizes (small: 8,9 l/min; big: 14,5 l/min at 330 bar) were studied with speeds of 2 and 4 km/h to investigate the influence of driving speed and reduced water output at the same water pressure [5].

3. Results

The trained and quantized *C. autumnale* detector was evaluated on a dedicated test dataset. In the context of site-specific weed control, it is more important to identify as many weeds as possible even at the cost of some false-positives. Only thus can a long-term reduction of the weed population be achieved. For this reason, we employ the so-called F2-score, which prioritizes the recall compared to the precision of the detector, to determine the decision threshold. Here the recall is the probability a weed in the ground truth dataset is correctly detected as such, whereas the precision is the probability that a given predicted bounding box is actually a weed, see [7] for more information. Since the section width of the tool is 0.25 m, the precise localization of the weeds is only of secondary importance. A true positive is thus defined if the area of the intersection divided by the area of the union (IoU) of the true and the predicted bounding boxes exceeds 50 %. With this, the detector achieved a precision of 50.7 % and a recall of 72.7 %, which results in an F2-score of 66.9 %.

Throughout the initial testing of the machine control the dummy target got hit every time, independent from driving speed and target variant. As shown in Table 1, however, the treated distance before and after the target varied. The nozzle activation at 4 km/h was the earliest for both target variants, corresponding with a short distance treated after the target. With increasing speed, the total treated distance gets lower. A discontinuous nozzle activation with several pulses along the activation window was observed in all cases.

Table 1: Results of the water-jet test with visual target detection

target variant	orthogonal			lengthwise		
speed, km/h	2	4	6	2	4	6
avg. treated distance before target, m	0.49	0.68	0.55	0.54	0.69	0.52
avg. treated distance after target, m	0.59	0.30	0.36	0.63	0.31	0.34
avg. treated distance total, m	1.18	1.08	1.01	1.41	1.25	1.11
SD treated distance total, m	0.06	0.10	0.17	0.05	0.08	0.11

The small nozzle variants showed less effectivity in reducing the visible plant population by the time of the hay cut in mid-June compared to the big nozzle variants, see Table 2. Considering two years for the latter variant, the reduction rates were greater or equal to 90 % regardless of the driving speed. The natural reduction indicated by the control plot variant differed between the years 2023 and 2024 and can be taken as indicators for the given weather conditions. Application speed seems to have a stronger impact on the small nozzle variant, while the big nozzle showed preferable reduction rates at both speeds. This also applied to the long-term reduction observed in the second year of the trial, where the small nozzle variant showed less effectivity and even an increase in plant population with the application speed of 4 km/h.

Table 2: Percentage reduction in the number of plants after the last treatment relative to start of season (2023 & 2024) and change of plant population before the first treatment in 2024 using water-jets with different nozzle size and varied speed

strategy	avg. reduction of plants 2023	SD	avg. reduction of plants 2024	SD	avg. change of plant population	SD
small nozzle, 2 km/h	65 %	0.282	45 %	0.170	-7.5 %	0.123
small nozzle, 4 km/h	71 %	0.211	32 %	0.271	4.2 %	0.179
big nozzle, 2 km/h	92 %	0.073	95 %	0.040	-23.9 %	0.139
big nozzle, 4 km/h	93 %	0.083	90 %	0.081	-21.4 %	0.154
control plots w/o treatment	44 %	0.194	28 %	0.201	9.1 %	0.242

4. Discussion

Given the difficulty of identifying green weeds on a grassland site, a reasonably good detection performance was achieved. Nevertheless, further optimizing the architecture and datasets should yield further accuracy gains. With the current approach each frame from the cameras is analysed individually. Incorporating some preceding frames might increase the detection rates, but with an increased cost in computational complexity and thus latency.

The results of the water-jet test showed that the theoretically determined parameters were correct for the control software in combination with the visual target detector. Offsets of the machine geometry and delay times fit for nozzle activation independent of the driving speed.

Target size is also correctly taken into account, which could be seen by a longer nozzle activation when the target was placed lengthwise. Because of the machine design there is a delay between valve switching and full power built up of the water jet at the ground. Mainly two factors are related to this: First, the tubing length between valve and nozzle and second the rotating nozzle design. The rotation of the nozzle is driven by the water pressure and flow through the housing. This leads to a dead time the nozzle has to be activated in advance of the target plant until the sought working state is reached. Due to more distance travelled per second the activation has to be even earlier when increasing the driving speed. Therefore, a fast activation is most important for sufficient cutting and shredding of the biomass. Deactivation of the nozzle can be done directly after passing the whole plant. An unnecessary long activation after the target plant raises the risk, that more sections of the machine get activated and the overall system pressure drops too low. The discontinuous nozzle activation observed in the test is related with the camera application software and has to be eliminated such that the nozzle stays on long enough for reaching the desired working state. Due to the simplified test design with a different nozzle type and low water pressure, deviating results could be possible for the real tool configuration. The findings are basis for the further machine control setup and adjustment for precise nozzle activation along with the visual detector. The effectivity of the nozzle variants in repressing *C. autumnale* is related with the water output per minute, which defines the aggressiveness and cutting ability of the water jet. There is a difference of approximately 5.6 l/min at 330 bar working pressure between both nozzle variants. The reduced cutting ability could be seen directly after treatment of the plots: The plants treated with the small nozzle were only partially cut or damaged, while being fully separated by the big nozzle, which is also currently used on the machine. Due to the rotating nozzle design a higher application speed means fewer possible hits of the jet on the plant. This effect seems to have more influence on the small nozzle variant and can be used to adjust the treatments intensity over speed [2]. Surprisingly the faster application speed showed more effectivity than the slow variant in 2023. Human errors during treatment or evaluation could be a possible reason for this.

5. Conclusion

The real-time weed detector demonstrated reasonably high effectiveness in identifying *C. autumnale*, with a recall of 72.7 %. With the current state of the machine control, it is possible to reliably hit a target, which was detected via the real-time plant detector, with the water jet while driving with speeds between 2 and 6 km/h. Future development is aimed towards a more harmonized nozzle activation to ensure a proper force distribution of the water jet and the optimal activation point in before a target will be determined. Field trials with a dynamic application of the water jet showed good results in reducing the plant population of *C. autumnale* by the time of the hay-cut when using the bigger nozzle. These findings support the treatment strategy for a mechanical control of *C. autumnale* and show a suitable design for the water hydraulic components used on the tractor mounted device.

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References

[1] Hoiß, B.; Berg, M. and Krämer, M.: Die Herbstzeitlose im extensiven Grünland. ANLiegen Natur 44/1, S. 123–126, 2022.

[2] Martin, F., Lohrmann, G. and Stoll, A.: Selective weed control in grassland using high-pressure water jets. VDI-Berichte Nr. 2395, LAND.TECHNIK/AgEng pp. 105-110, 2022.

[3] Petrich, L., Lohrmann, G., Neumann, M., Martin, F., Frey, A., Stoll, A. and Schmidt, V.: Detection of Colchicum autumnale in drone images, using a machine-learning approach. Precision Agriculture 6/21, pp. 1291-1303, 2020.

[4] Haußmann, I-L., Petrich, L., Lohrmann, G., Schmidt, V. and Stoll, A.: Bilddatenakquisition zur Entwicklung eines Machine-Learning-Detektors für Grünlandunkräuter. Tagungsband 44. Jahrestagung der Gesellschaft für Informatik in der Land-, Forst- und Ernährungswirtschaft, 27.-28.02., pp. 287-292, 2024.

[5] Haußmann, I-L, Lohrmann, G. and Stoll, A.: Untersuchung zur Zurückdrängung von Herbstzeitlosen (C. autumnale) mit einem wasserhydraulischen Verfahren. 17. Wissenschaftstagung Ökologischer Landbau, Gießen, Deutschland, 05.-08.03.2024.

[6] Tan, M., Pang, R., and Le, Q.V.: EfficientDet: Scalable and Efficient Object Detection. In 2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2020, pp. 10778-10787.

[7] Hastie, T., Tibshirani, R., and Friedman, J.: The Elements of Statistical Learning. New York: Springer, 2009.