Toward Autonomous Mobile Robot Navigation in Early-Stage Crop Growth

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Abstract: This paper presents a general procedure for enabling autonomous row following in crops during early-stage growth, without relying on absolute localization systems. A model based on deep learning techniques (object detection for wide-row crops and segmentation for narrow-row crops) was applied to accurately detect both types of crops. Tests were performed using a manually operated mobile platform equipped with an RGB and a time-of-flight (ToF) cameras. Data were acquired during different time periods and weather conditions, in maize and wheat fields. The results showed the success on crop detection and enables the future development of a fully autonomous navigation system in cultivated fields during early stage of crop growth.

1 INTRODUCTION

Autonomous vehicles for agriculture have drawn the attention of farmers in recent decades and the activity for developing robust, safe and eco-friendly autonomous vehicles has increased significantly (Gonzalez-de-Santos et al., 2020). However, navigation is still a current challenge for autonomous robotic systems (Sarmento et al., 2021) because agricultural fields are unstructured, dynamic and diverse environments where weather conditions, luminosity, and stages of crop growth change continuously.

Conventional localization and perception technologies, such as the Global Navigation Satellite System (GNSS), 2D and 3D LIDAR, and stereo cameras, have proven their usefulness in ensuring autonomous navigation in fields (Shalal et al., 2013). Although they rely heavily on user intervention to ensure accurate mapping and conditioning of the working environment, they are not able, by themselves, to develop a robust navigation system capable of ensuring full autonomy in these demanding environments. Precise mapping (including crop location), setting up the working area, luminosity variability, GNSS correction signal failure, communications latency, and GNSS-denied zones are currently some of the major challenges in autonomous navigation.

Weed management is one of the operations that has generated the most solutions in agriculture (Oliveira et al., 2021). Machine vision and GNSS-based mapping have been the preferred technologies to distinguish weeds from crops and deliver precision treatment (Mavridou et al., 2019). Site-specific weed management techniques have gained considerable popularity in the last few years, particularly those based on high-power laser sources, which offer a more sustainable and eco-friendlier alternative than the other techniques (Rakhmatulin & Andreasen, 2020). These technologies have been shown to be successful when weeds (and therefore crops) are in an early stage of growth. Crop row following has been a widely discussed topic in the literature (Bonadies & Gadsden, 2019). However, most of the studies and applications solve the problem when the crop is already in a mature growth stage or in crop types with an appropriate morphology for LIDAR-based methods, such as vineyards (Emmi et al., 2021). The early plant stage growth, together with the unevenness in ground height and the presence of weeds, make conventional perception systems unable

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to identify the crop properly, thus preventing its further use for autonomous row guidance.

This paper presents an approach for developing smart perception systems to enable autonomous robots to navigate in cultivated fields in an early stage of crop growth without relying on absolute localization systems, such as GNSS.

2 RELATED WORK

Autonomous navigation in crop field is mainly composed by following the crop lines, and at the end of each pass, making a U-turn to return to the field. The identification and following of crop rows are subjects that still attract considerable interest. Diverse strategies are found in the literature to solve these problems that follows a quite general procedure: **(i)** single crops or crop rows are detected; **(ii)** the crop row central point or the equation of the line is extracted; and **(iii)** the path to be followed by the mobile system is planned and executed. The techniques commonly used for identifying the crop rows are mainly based on a combination of binary segmentation, greenness identification (Woebbecke et al., 1995), morphological operations, Otsu's method (Otsu, 1979), and edge detection techniques, such as the Hough transform (Hough, 1962). Many studies have made use of these techniques across different types of crops. For example, Jiang & Zhao, (2010) applied these techniques to identify the crop lines in a soybean field. Romeo et al., (2012) developed an algorithm based on green pixel accumulation for extracting crop lines in a maize field that outperformed the Hough transformation methods.

To increase the accuracy and robustness of these techniques, Jiang et al., (2015) proposed a method based on least squares and multiple regions of interest (ROIs), where the data were split into horizontal strips. They compared their proposal with the standard Hough transform on soybean, wheat and maize crops. Following the same strategy, Zhang et al., (2018) applied a multi-ROI approach in a maize field. As a novelty, they employed double thresholding approach, using the Otsu method in combination with particle swarm optimization to improve the differentiate between weeds and crops. There are also several studies that combined the absolute navigation systems and computer vision techniques previously mentioned. For example, Bakker et al., (2011) employed an RTK-DGPS system to navigate in a sugar beet field, and Kanagasingham et al., (2020) proposed a combined navigation strategy for a rice field weeding robot.

For vineyards and orchards in general, it is quite common to use LIDAR-based systems in combination with IMU data and odometers (Lan et al., 2018) or color cameras (Benet et al., 2017) for crop row following. The latest technological advances have made it possible to incorporate other technologies to obtain 3D information from the environment, as is the case with infrared-based cameras. Among these cameras, there is a growing interest in the time-of-flight (ToF) cameras, that provides a point cloud of the environment in a manner that is similar to the way that LIDAR does. Gai et al., (2021) used this type of camera for navigation under a canopy, where the GNSS signal may be denied. Currently, as the above work stated, ToF cameras are beginning to be used with great interest in outdoor environments due to improvements in their light sensors and wider vertical field-of-view (FoV) capability than what is available with LIDAR sensors.

There are many research studies that use classical techniques for in-field navigation, but these techniques usually need to adjust certain system parameters for navigating in new environments and situations, which limits their generalizability. In addition, for methods based on green detection, the presence of weeds may be a major problem.

In recent years, techniques based on artificial intelligence (AI) have gained much interest. Two different techniques can be distinguished: **(i)** object detection, which uses bounding boxes to identify the classes, and **(ii)** segmentation, which is based on pixel classification. Their selection depends on the type of crop to be identified: **(i)** wide row crops (maize, sugar beet) where the object detection is preferred and **(ii)** narrow row crops (wheat, rice) where segmentation-based classification is more suitable. Normally, artificial intelligence-based techniques are used to identify the crop, and then, some combination of the aforementioned techniques, such as the Hough transform or RANSAC (Fischler & Bolles, 1981), are used to extract the crop lines. Ponnambalam et al., (2020) used a SegNet (Badrinarayanan et al., 2017) with ResNet50 (He et al., 2015) convolution neural network (CNN) in combination with a multi-ROI strategy to segment and extract the row crops in strawberry fields. Simon & Min, (2020) compared the results of a method based on a neural network with the classical method based on the Hough transform in a maize field. The deep learning method obtained higher accuracy and more robustness. Emmi et al., (2021) used a YOLOv3 (Redmon & Farhadi, 2018) network for object detection in broccoli, cabbage and vineyard trunks. de Silva et al., (2021) tested the performance of a deep learning model based on U-

Net (Ronneberger et al., 2015) in a sugar beet field under different scenarios, such as shadows, presence of weeds, gaps in the crop row, intense sunlight conditions, and different stages of crop growth. There is also a special interest in AI on the edge, i.e., on users' devices. For this purpose, MobileNet (Howard et al., 2017) networks are the most suitable due to their efficiency and speed, with the counterpart having generally poorer accuracy.

In the search for new alternatives to weed management, strategies based on high-power lasers have emerged. This type of solution has been shown to be subtle when plants are small (Rakhmatulin & Andreasen, 2020). These types of strategies have given way to alternatives for row following, where the abovementioned examples may not achieve accurate results and the robustness of the models may be inadequate. To generalize the problem, it is necessary define what an early-stage crop is. There are different nomenclatures to define the different growth stages of different crops, but these definitions are normally specific to each type of crop. For the sake of this development, maize and wheat are selected as examples of crops sown in wide rows and narrow rows, respectively, which coincide with this case study. The growth stage in maize will be identified using the classification made by (Zhao et al., 2012), while the classification made by (Zadoks et al., 1974) will be used for wheat. In this paper, early growth stage crops will be considered as those from the moment the perception system is able to detect them until the moment of growth when the weeding system based on high-power laser sources is no longer efficient for the elimination of weeds, assuming that crops and weeds grow at the same rate. This stage corresponds to approximately the V2 stage for maize (Zhao et al., 2012) and approximately the 12-seedling stage for wheat (Zadoks et al., 1974).

The literature on autonomous navigation in the early growth stage crops is rather scarce, although there are some significant studies. For maize, Wei et al., (2022) built what they defined as the dataset row anchor selection classification method (RASCM) for tracking crop rows. García-Santillán et al., (2018) developed a method for extracting curved and straight crop rows based on greenness identification, double thresholding and morphological operations that was also tested in what one can consider early-stage maize crops. Winterhalter et al., (2018), assuming that crop rows are parallel and equidistant, proposed a method based on an adaptation of the Hough transform that was able to detect crop rows in early-stage sugar beet crops. Finally, Ahmadi et al., (2021) developed a method based on greenness identification and Otsu's method for multicrop row detection relying only on on-board cameras. This proposal was tested in early-stage sugar beet.

Therefore, this paper presents a strategy that integrates several of the technologies mentioned above, such as artificial intelligence for crop detection, in conjunction with emerging perception systems such as ToF cameras, to obtain a highly accurate depth map and locate the detected crop with respect to the mobile platform. The present work aims to pave the way for the development of a system able to autonomously navigate in cultivated fields in an early stage of crop growth in a robust and efficient way, with the capability to scale the system to incorporate new crops or to be able to operate in unforeseen environments.

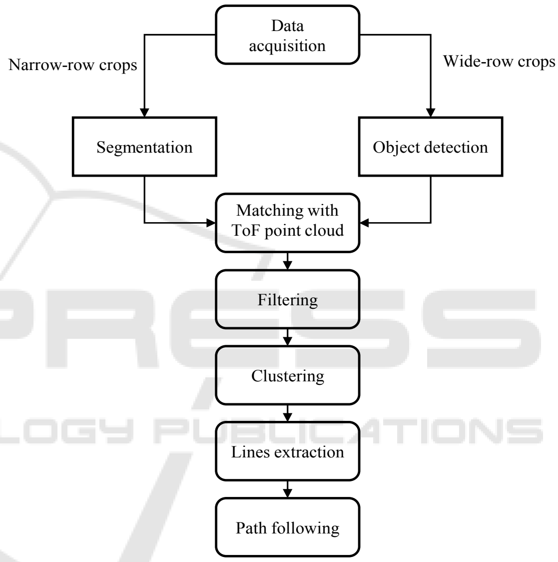

Figure 1: Diagram of the presented methodology.

3 MATERIALS AND METHODS

Figure 1 presents a general procedure for enabling autonomous navigation in crops in an early growth stage. First, data are acquired by the perception systems, which consist of RGB and ToF cameras. Then, depending on the type of crop, a different approach is followed. For wide-row crops, object detection is used, and for narrow-row crops, segmentation is applied to identify the crops in the RGB images, making use, in both cases, of deep learning models. Once a crop is identified, a match between the ToF point cloud and the output of the respective deep learning model is made, obtaining the relative distance between the detected crops and the autonomous vehicle. Next, a filtering process is utilized to remove the outliers and the noise of the matched point cloud, mostly produced by the sunlight. Next, RANSAC is applied to obtain the ground plane, the background points are removed, and the points that correspond to the crops are projected onto the plane. Later, a clustering algorithm based on DBSCAN (Ester et al., 1996), using the present and past points, is employed to obtain the crop rows. Finally, the RANSAC algorithm is again applied to compute the directions of each cluster, and the final path that the mobile platform must follow is calculated.

For crop identification, depending on the type of crop, a different deep learning architecture was used. In the case of maize, the YOLOv4 (Bochkovskiy et al., 2020) model was employed to detect the plants. For wheat, several combinations between the segmentation models PSPNet (Zhao et al., 2017), U-Net (Ronneberger et al., 2015), and SegNet (Badrinarayanan et al., 2017) and the base models ResNet50 (He et al., 2015), VGG16, MobileNet (Howard et al., 2017) and CNN were tested (see Table 1). Their performance characteristics and comparisons of the results of the different models will be discussed in the results section.

Table 1: Segmentation models.

	Base Model	Segmentation Model
1	CNN	PSPNet
2	VGG16	PSPNet
3	ResNet50	PSPNet
4	CNN	U-Net
5	VGG16	U-Net
6	ResNet50	U-Net
7	MobileNet	U-Net
8	CNN	SegNet
9	VGG16	SegNet
10	ResNet50	SegNet
11	MobileNet	SegNet

Figure 2: Example of the maize experimental fields.

Figure 3: Example of the wheat experimental fields.

The presented methodology was validated under the European project named Sustainable Weed Management in Agriculture with Laser-Based Autonomous Tools (WeLASER). The WeLASER project is a consortium of ten partners from Spain, Germany, Denmark, France, Poland, Belgium, Italy and the Netherlands. WeLASER aims to develop precision weeding equipment based on applying lethal doses of energy to weed meristems using a high-power laser source with the main objective of eliminating the use of herbicides while improving productivity. The prototype consists of an autonomous robot with an artificial intelligent vision system that will differentiate between weeds and crops. It will then detect the meristems of the weeds and apply the laser to kill the plants. All the systems will be coordinated by a smart controller based on the Internet of Things (IoT) and cloud computing techniques. The target crops will be wheat, maize, and sugar beet (WeLASER, 2022).

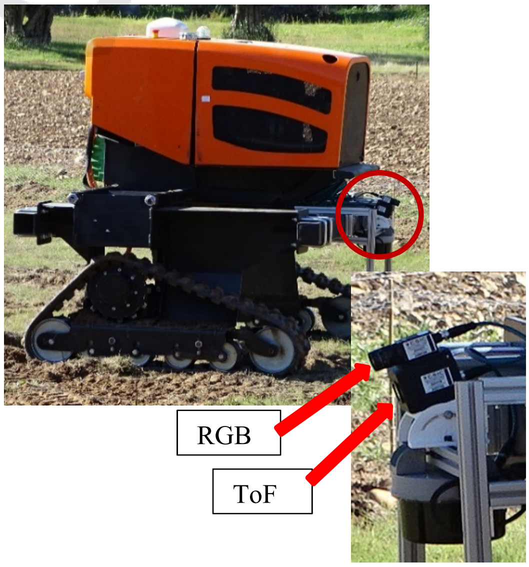

Figure 4: CAROB robotic platform and perception system.

To validate the presented algorithm, data were acquired in experimental fields of maize (see Fig. 2) and wheat (see Fig. 3). The dimensions of each field were 20 m × 60 m.

The CAROB robotic platform that was developed by AgreenCulture (2022) was used for data acquisition, where the perception system was installed (see Fig. 4). The perception system consisted of an RGB camera TRI016S-CC RGB equipped with the SV-0614V lens (resolution: 1.6 MP; FoV: 54.6° × 42.3°), and a ToF camera HLT003S-001 (resolution: 0.3 MP; FoV: 69° × 51°), of which both were acquired from Lucid Vision Labs (2022).

The data were acquired by manually operating the mobile platform during different time periods and weather conditions in the same season. To build the maize and wheat datasets 450 and 125 images were labeled, respectively, using data augmentation techniques, such as rotating, image cropping, blurring and brightness changes, among others, were used to increase the size of the dataset. In both cases, 80% of the data was destined for the training group, 10% for the validation group and 10% for the test group. Part of the dataset used in this work has been published in an open-access repository, for both maize (https://doi.org/10.20350/digitalCSIC/14566) and wheat (https://doi.org/10.20350/digitalCSIC/14567). As shown in Fig. 5, depending on how the labeling process is performed, this can lead to misleading errors. In the dataset images, the crops that are located in more distant regions or that are not clearly recognizable have not been labeled. Consequently, when the model was validated, in these regions false-positives were detected, although they were unlabeled crops, but because they had not been previously labeled, the model would consider them as false positives, decreasing the real performance of the model. An alternative to mitigate this common problem, ignoring masks, was used by specifying that the model not consider these parts of the images where the differences between crops and the background may be ambiguous.

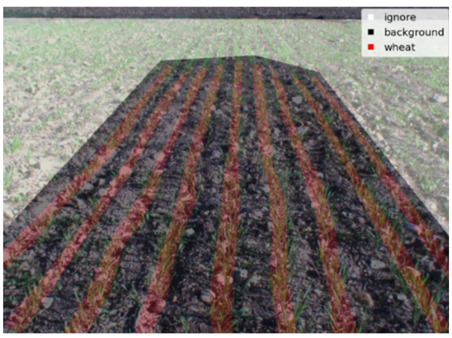

Figure 5: Example of a labeled wheat image.

The segmentation models were implemented with Keras (https://github.com/fchollet/keras) using TensorFlow (Abadi et al., 2016) as the backend software tool, while the YOLOv4 model used Darknet (Redmon, 2013) version. The training process was performed on a Quadro RTX 6000 graphics card with 24 GB GDDR6 of RAM memory, while the inference process was evaluated using GeForce GTX 1650.

Table 2: Performance of the segmentation models.

Model	IoU	Training time [s] per epoch
MobileNet SegNet	0.6815	124
MobileNet U-Net	0.7347	124
ResNet50 PSPNet	0.7370	180
ResNet50 SegNet	0.7578	164
ResNet50 U-Net	0.7406	183
VGG16 PSPNet	0.7343	227
VGG16 SegNet	0.7461	196
VGG16 U-Net	0.6982	208
CNN PSPNet	0.7321	171
CNN SegNet	0.7364	156
CNN U-Net	0.7339	155

4 RESULTS

To assess the overall performance of the presented methodology, it is first necessary to evaluate the crop identification models. For the wheat crop, the different models listed in Table 1 have been compared. All models were trained for the same initial number of epochs, although an early stopping technique based on validation loss was applied to avoid overfitting. The comparison between the different segmentation models is summarized in Table 2. As the dataset was imbalanced, the metric chosen to evaluate the performance of the models was a frequency weighted intersection over union (IoU) determination. The model with the best performance was ResNet50-SegNet. However, in these types of applications in which the models are going to be used in real time, apart from evaluating the performance of the model, it is necessary to consider their inference time. In this case, the differences between the inference times of the considered models were not notable, taking as a basis that, in general, the inference time is smaller than the training time. Hence, the final model that has been selected was the aforementioned model. As expected, models based on MobileNet are considerably faster, but at the cost of a generally poorer performance.

An example of the typical training curves is presented in Fig. 6, for the training with the ResNet50-SegNet network, where the loss curves for both training (train_loss) and validation (val_loss) are presented.

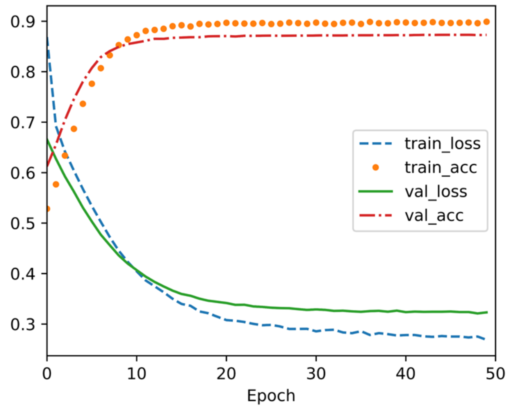

Figure 6: Example of training curves. Y-axis normalized to compare loss curves and precision curves.

It can be seen in these curves that the network has not been overfitted, the validation samples are representative. Moreover, it can be seen that a point is reached from which the training loss continues to decrease, although the validation loss remains the same. Furthermore, Fig. 6 presents also the accuracy curves for both train (train_acc) and validation (val_acc) which shows a proper fit of the model.

On the other hand, regarding object detection in maize, a YOLOv4 model was selected for crop identification. Average precision (AP) was the metric chosen to assess the performance of the model, and its values for IoU thresholds of 0.25, 0.5, and 0.75 were 0.9168, 0.8478 and 0.1496, respectively. In addition, the precision and recall metrics have been calculated for different thresholds, and the comparative curves are presented in Fig. 7.

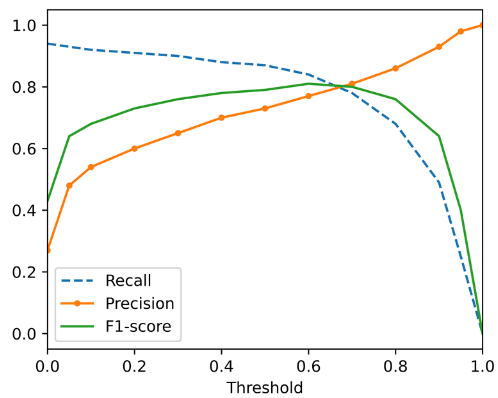

Figure 7: Recall, precision and F1-score for different threshold values. Y-axis normalized.

The threshold is be chosen depending on whether the recall or precision is desired to be higher, i.e. whether a higher number of false positives (FP) or false negatives (FN) is preferred. A trade-off between precision and recall is selected based on the F1-score, which is maximal for threshold values of approximately 0.6.

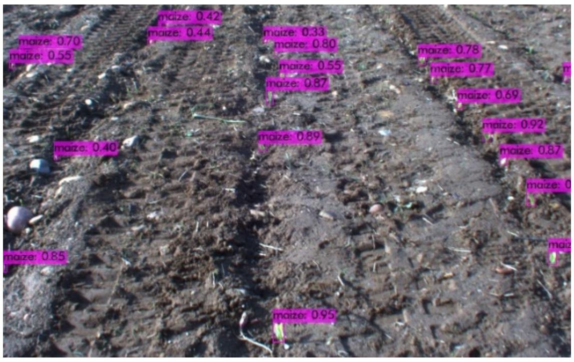

Figure 8: Output of the object detection model (maize).

In both cases, the models are capable of properly detecting the crops (see Fig. 8 and Fig. 9), thus enabling crop line extraction. It is worth mentioning that for autonomous navigation, the detection of all crops in a single image is not an essential requirement, given that strategies such as point accumulation or particle filters can be applied to reconstruct the crop line by taking information from various epochs. In the absence of ground truth of the row crops, a quantitative evaluation of the error obtained by the process of crop line extraction is not feasible.

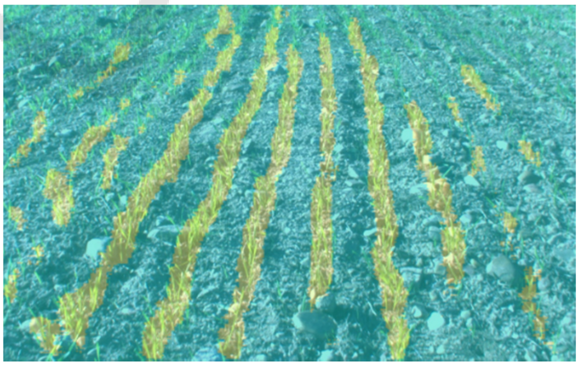

Figure 9: Output of the segmentation model (wheat).

One could consider that the error will be similar to the error obtained by other studies that have used a similar procedure for line extraction, such as the work presented by Emmi et al., (2021). Although the error cannot be quantified (because at the time of the tests the position of each crop was not available), it can be clearly established that the presented methodology is able to identify the crop lines properly (see Fig. 10).

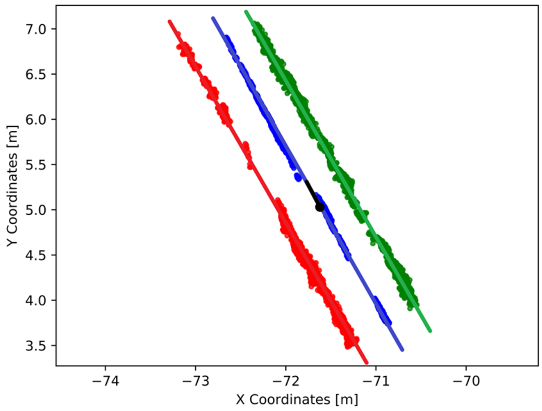

Figure 10: Clustering and lines extraction (maize).

Figure 10 presents the result of the application of the methodology presented in Fig. 1, and by using a line extraction such as RANSAC, it is possible to extract the crop lines for the maize field, where the position and direction of the mobile platform are represented in black color in a cartesian coordinate frame. Finally, the results have shown the effectiveness of the presented methodology for autonomous navigation in early-stage crop growth.

5 CONCLUSIONS

A general procedure for crop-row identification in early-stage growth has been presented. This methodology seeks not to depend on global localization systems, which will enable robust autonomous row following in both wide-row crops and narrow-row crops. The methodology is based on crop identification using state-of-the-art deep learning models, validated in maize and wheat at an early growth stage, although the methodology can be extended to many more crops. This approach demonstrates that it is possible to integrate in a single methodology the identification and classification of diverse wide-row and narrow-row crops to estimate the row lines for later navigation while eliminating the outliers. The presented method has been validated using offline data gathered by a robotic platform during different real working conditions. The results show the robustness and effectiveness of the methodology in identifying the crops, and later obtaining the characterization of the crop lines, even considering their early stage of growth. The presented approach will enable the future development of a fully autonomous navigation system for weed management using high-power laser technology. Future work will aim to expand the identification capacity for other crops, such as sugar beet, which is one of the target crops of the WeLASER project, as well as to validate the presented methodology in real time.

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