# Robotic Green Asparagus Selective Harvesting

Adrian Leu, Mohammad Razavi, Lasse Langstädtler, Danijela Ristić-Durrant, Holger Raffel, Christian Schenck, Axel Gräser, and Bernd Kuhfuss

***Abstract*—Robotic harvesting in the open field demands innovative solutions in robot perception and mechanics to cope with environmental challenges. In this paper, a prototype robotic harvester that is able to cope with the challenges of selective harvesting of green asparagus is presented. The harvester is able to drive along an asparagus dam in the field, detect asparagus stalks, identify stalks that are ready for harvesting, and perform harvesting without damaging. These system abilities are enabled by a novel vision perception module and a novel harvesting mechanism. The perception module is based on three-dimensional-point cloud processing, and it is able to reliably and robustly detect the asparagus stalks, their positions, and dimensions. A novelty of the proposed harvesting mechanism is a multi-tools solution to increase harvesting productivity. The results of the first outdoor field tests demonstrate the applicability of the presented robotic harvester.**

***Index Terms*—Agricultural robotics, green asparagus selective harvesting, robot vision, robotic harvesting system.**

## I. Introduction

ROBOTIC systems have been actively developed over the past three decades to automate the harvesting process [1], [2]. The automation has been motivated by replacing the hard manual harvesting process, by high labor costs as well as by other social, environmental, and food quality aspects. The continued development of robotic technologies such as mechatronics and perception has been successfully applied in harvesting systems. However, despite these developments, harvesting robots are still far from mature, and harvesting is still predominantly manual due to the limited performance of current robots. A comprehensive review article that analyzes state-of-the-art and future perspectives for harvesting robots in high-value crops is [3]. The complexity of the crop environment forms the main bottleneck to better performance of harvesting robots. There are four production environments: 1) orchard; 2) greenhouse; 3) indoor; and 4) open field. Each of these environments, in which the robot must operate, provides a lot of variation. In contrast to greenhouses and indoor, where the controlled environmental conditions could be achieved for consistent plant development, in open fields variations, variable lighting conditions are more highlighted. Besides this, the wind and rain protection is needed and, also, navigation in orchards and the open field is more challenging because robots have to rely on guidance systems, whereas in greenhouses and indoors robots can drive on rail systems.

Alongside the environmental conditions, further challenges for harvesting robotic systems concern crops variations. A crop varies in position, size, shape, and reflectance due to the variation that exists in nature. For example, the shapes of the fruit vary: sweet peppers are cylindrical, but the width/height ratio is not constant; tomatoes can be round or elongated, and they vary in size. As a result, sensory techniques of harvester robots must cope with this variation. Further challenges for crop detection regarding the position, shape, size, reflectance, and texture are discussed in [4].

A review of different projects dealing with automation of different crops harvesting is given in [3]. Most projects were aimed at tomato, orange, apple, or asparagus harvesting. Automation of asparagus harvesting is the topic of this paper as a novel robotic harvester developed to cope with challenges of selective green asparagus harvesting is presented.

There are several works published on robotic asparagus harvesters as reviewed in [1]. In [5], an integrated robotic system that is able to move in the field, identify white asparagus stems, grasp them, and then cut accordingly without any physical damage is presented. The cultivation characteristics of white asparagus are different from the green one since it grows below the surface of the ground as opposed to green asparagus which grows above the surface of the soil. This, however, influences that a robotic white asparagus harvester is characterized with different perception and gripper technologies than that of a robotic green asparagus harvester.

Research on green asparagus harvesting mechanization started in the early 1950s. However, labor costs were relatively low and there was no interest in investing in machines. In the 1990s, increasing costs of labor associated with lower availability contributed to restarting the research on mechanization of asparagus harvesting with development of new prototypes and field trials [6]. Green asparagus harvesters are classified based

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A. Leu, M. Razavi, D. Ristić-Durrant, and A. Gräser are with the Institute of Automation, University of Bremen, Bremen 28359, Germany (e-mail: aleu@iat.uni-bremen.de; mrazavi@iat.uni-bremen.de; ristic@iat.uni-bremen.de; ag@iat.uni-bremen.de).

L. Langstädtler, C. Schenck, and B. Kuhfuss are with the Bremen Institute for Mechanical Engineering, University of Bremen, Bremen 28359, Germany (e-mail: langstaedtler@bime.de; schenck@bime.de; kuhfuss@bime.de).

H. Raffel is with the Bremen Center of Mechatronics, Bremen 28359, Germany (e-mail: raffel@mechatronik-bcm.de).

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on how the asparagus product is harvested. The nonselective mechanical harvesters harvest all the asparagus standing in the field. In contrast, the so-called selective harvesters cut and collect only those asparagus stalks which have reached a marketable length, without damaging the immature stalks requiring a further couple of day's growth. Consequently, the selective harvester demands more advanced technology than nonselective harvesters. Arndt *et al*. [7] discussed the trends and developments of an automated selective asparagus harvesting robot that has been operational at the Centre for Advanced Manufacturing and Industrial Automation (CAMIA), University of Wollongong, Australia. Using microprocessor technology, CAMIA machine is able to select and remove asparagus stalks of predetermined height, leaving anything shorter to future harvesting. The machine contains rotating pairs of discs each with a separate detection system and a separate knife. In the harvester described in [7], six pairs of discs are used along with beam detection through fiber-optic photoelectric sensors. The harvester operates on the principle that when the asparagus stalk breaks the sensor beam, signals from the sensor as well as the distance counter are sent to the programmable logic controller (PLC). When the correct traveling distance is reached, the controller actuates a valve causing the pneumatic cylinder to push the cutting knife down and rotate it from the vertical to the horizontal cutting position. The stalks that are too short to break the light beam remain uncut. CAMIA was invited to send its prototype to the USA in May 1995 to participate in field trials being conducted by the Washington Asparagus Commission in one of the two major asparagus growing regions in the US. Among others, the performed field tests showed that CAMIA, which was tailored to harvest asparagus dams of type used in Australia, was not able to adjust to types of the dams used in the US and so was not able to cut stalks of less than 20 cm in height.

Another example of selective harvester is the Kim Haws harvester which relies on light-beam sensor to detect the asparagus similar to CAMIA's harvester [8]. When the self-propelled, four-wheeled machine goes over a row of asparagus plants, the taller stalks trip the sensor. When a stalk breaks the light beam, a mechanism is dispatched to cut that stalk and throw it onto a conveyor belt. The stalk is carried to a sorting table on top of the machine, where human workers either sort it or, if it is unacceptable, leave it on the belt—which drops it back on the ground. In different performed field test, CAMIA and Haws harvesters as well as other selective harvesters such as Geiger-Lund selective mechanical harvester [6] performed relatively well but because of some problems with the reliability of the used sensors, the machines missed many asparagus stalks and caused more above ground damage than manual harvester. These results indicated that, although significant advances have been made, automated asparagus harvesting technologies still require further refinement before they are economically competitive with manual cutting. To realize such refinements, selective harvesting needs to benefit from the exploitation of further improvements in specific robotic technologies such as perception, mechatronics, and navigation.

A research group of the Robotics Institute at Carnegie Mellon University developed MANTIS–Automated Asparagus Harvester [9]. MANTIS harvester uses onboard LIDAR to detect nearby asparagus in range. LIDAR sensor resolves the asparagus stalks as points for the robot planning system to use to move the end-effector. The end-effector subsystem both cuts the asparagus as well as contains a secondary IR sensor system that localizes the asparagus for cutting. However, experimental trials showed that the MANTIS accuracy was worse than expected. The errors from the LIDAR sensor compounded with the errors in the mechanical design, making the system too inaccurate to harvest asparagus effectively. Authors concluded that with slightly better sensor accuracy, system performance would have improved greatly. The better results were published on using the vision sensors. Irie *et al*. [10] presented a green asparagus harvesting robot coordinated with three-dimensional (3-D) vision sensor to support manual harvesting of young asparagus, whose size is between 230 and 330 mm in length, in the asparagus cultivation furrow in a greenhouse. However, the perception and gripper technology of this robotic system as applied in greenhouse production environment is not feasible for an open field production environment due to much different asparagus growing conditions [11].

This paper presents the prototype of a novel robotic system for selective open field harvesting of green asparagus, which was developed with the aim to overcome problems of existing robotic asparagus harvesters. The presented robotic harvester is the result of the research, development, and evaluation of two projects. The underlined projects are the previously completed FP7 projects AmLight-Development of an automatic harvesting system for green asparagus with stalk detection in ambient light [12] and the current project GARotics [13]. GARotics comprises experiments, open field tests, within the ECHORD++ project. Results of the first open field tests are given in this paper which is particularly relevant because a harvesting robot must eventually be implemented under field conditions.

## II. GARotics System for Selective Harvesting

Asparagus is a fast growing plant cultivated on large fields with parallel dams and it is generally harvested daily during the production season since the asparagus reaches the desired size in a couple of days, which reflects the complexity and uniqueness of the asparagus cultivation process. When asparagus stalks reach a mature height of 12.7–15.24 cm, they release an enzyme that spurs the production of more stalks [14]. If young stalks are damaged before maturity, they will not produce the enzyme and the plant will die. Harvesting mature stalks without damaging surrounding shorter plants is difficult because asparagus stalks tend to cluster and the tenderness of the stalk makes it susceptible to breaking. Also, the challenge of asparagus harvesting is exacerbated by the rapid rate of growth of asparagus. If it is not harvested in a specific time frame when the stalks are between 15.24 and 20.32 cm, it will not be acceptable for the market. All these issues create challenges for an advanced, electromechanical system for selective harvesting that would allow asparagus farmers to decrease their dependence on seasonal labor and allow them to increase the productivity.

In this paper, a prototype of a novel robotic selective asparagus harvester is presented. The prototype was developed so to cope with above-mentioned challenges of selective

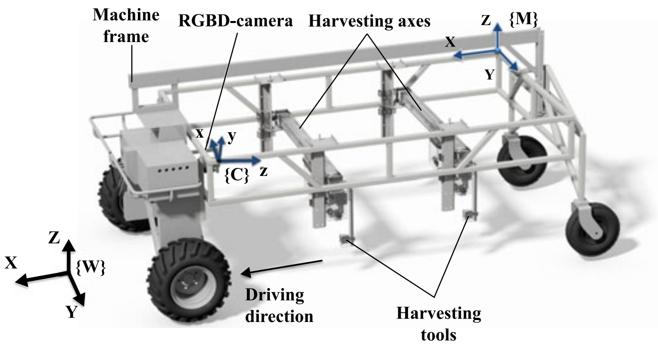


Fig. 1. Robotic system for green asparagus selective harvesting.

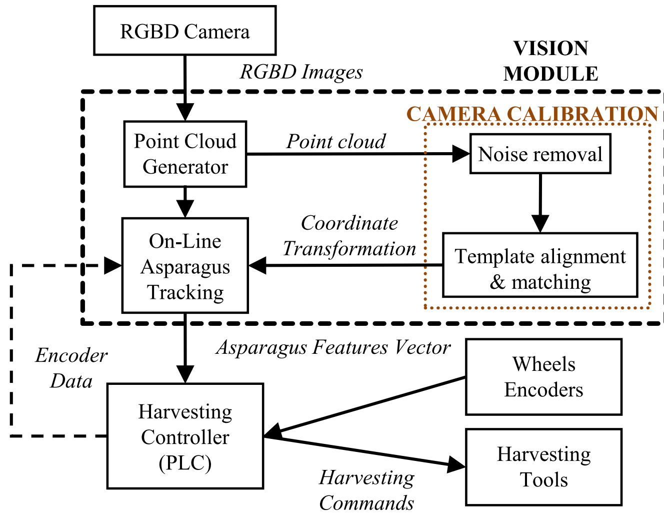


Fig. 2. Hardware and software architecture of the green asparagus harvesting machine including the vision module.

harvesting in open fields. This includes vision sensory system able to reliably and robustly recognize the size of asparagus stalks so to distinguish between asparagus ready for harvesting and not ready ones. Robustness against environmental conditions, such as variable lighting conditions, which cause color variations, has been achieved using the camera technology, an active time-of-flight sensor, which enables using of depth information independently of color. Reliable depth information is necessary for the reliable calculation of asparagus stalk position. Also, the proposed vision module incorporates calibration which leads to robustness against changes in camera orientations due to mechanical vibrations caused by driving over the rough terrains.

The rough terrain of an asparagus field was also a challenge for mechanics of the presented harvesting system. The machine is exposed to different ambient conditions (dust, sand, and water) that have to be endured by the actuation, gearing parts, and guiding elements. The harvesting tool was designed such that the size and motion possibilities enable the selectiveness in the harvesting by reaching and grabbing the detected asparagus stalk without the collateral damage of close by stalks. This newly developed mechanism is described in detail in Section IV.

The presented prototype incorporates a multitools solution to increase harvesting productivity. In this paper, the solution with two harvesting tools able to precisely move to the detected stalks and also to transport the harvested stalks to a storage system is presented. However, the inclusion of more tools would be easily possible by multiplying the harvesting axes within the machine frame.

## A. Harvesting Machine

The robotic system for selective harvesting of green asparagus is shown in Fig. 1. It consists of an RGBD vision sensor, two harvesting tools, which can move along $z$- and $y$-axis of the world coordinate system $\{W\}$, and a driving mechanism that enables the harvesting machine to continuously drive along an asparagus dam in positive $x$-direction at the predefined speed of 0.2 m/s. The RGBD vision sensor captures the asparagus dam scene in a direction opposite to the driving direction. Based on the vision information, the vision module recognizes a target asparagus as one which has the desired length for the harvesting and measures the 3-D position of the target asparagus. This information is sent to the harvesting controller, which issues appropriate commands to the harvesting tools, in order to perform the harvesting of the recognized target asparagus stalks.

As important for the development of the control system, besides the world coordinate system, a machine coordinate system $\{M\}$ and camera coordinate system $\{C\}$ were defined as well as shown in Fig. 1.

## B. Harvesting Control System

Fig. 2 shows a layout of the hardware and software architecture of the asparagus harvesting machine. The Microsoft Kinect v2 RGBD camera, used for the perceiving of the asparagus dam scene, provides a color image as well as a depth image. These two images are combined by the vision module into a point cloud, which is then used to detect the asparagus stalks' positions, as well as properties such as their sizes. Based on the asparagus size, the vision module determines which asparagus is ready to be harvested and sends the corresponding asparagus stalks' positions to the harvesting controller, which runs on a PLC. The harvesting controller is responsible for the control of the two harvesting tools as it decides which of the two tools shall harvest particular detected asparagus. Namely, the "free" tool which is closer to the asparagus detected at a particular location is chosen by the controller for the harvesting.

In order to know how far the harvesting machine traveled along the asparagus dam, the harvesting controller continuously receives encoder data from the wheels' encoders. This information is needed to determine a time moment when a certain $x$-position has been reached by a harvesting tool.

The output of the vision module, as it will be described in details in Section III, is an asparagus features vector of the format $\{\mathrm{ID}_i,\ x_{Mi},\ y_{Mi},\ \mathrm{Enc}_i\}$, $i = 1 \ldots n$, where $n$ represents the number of currently tracked asparagus stalks. The features vector for each detected asparagus $i$ contains its unique ID, its $x_{Mi}$ and $y_{Mi}$ coordinates in machine coordinate system, as well

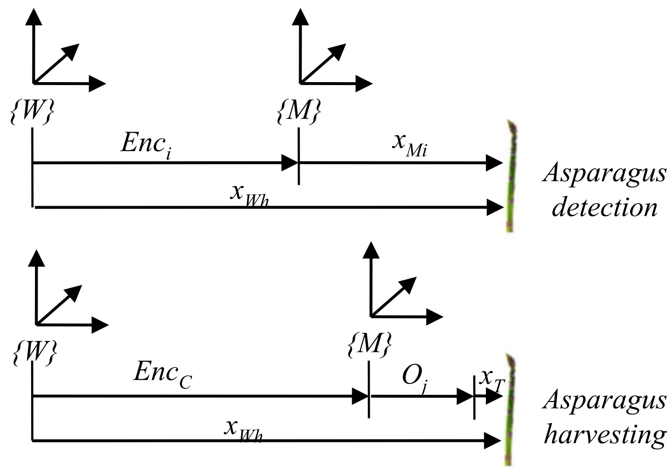


Fig. 3. Calculation of the harvesting distance at the time of asparagus detection (top). Determination of the start of asparagus harvesting (bottom).

as the encoder value $\mathrm{Enc}_i$ at the time when the scene image was recorded.

Using the asparagus features vector as the input, the harvesting controller computes the harvesting distance $x_{Wh}$ for each asparagus in the world coordinate system $\{W\}$, in order to decide which tool should harvest the particular detected asparagus. The harvesting distance is computed using the asparagus position $x_{Mi}$ with respect to the machine coordinate system $\{M\}$ and the encoder value $\mathrm{Enc}_i$ at the moment when the asparagus position was detected by the vision module:

$$x_{Wh} = \mathrm{Enc}_i + x_{Mi}. \quad (1)$$

The calculation of the harvesting distance for the detected asparagus $i$ is illustrated in Fig. 3 (top). The calculated harvesting distance is further used for determination of the moment when the harvesting process should be started. This is illustrated in Fig. 3 (bottom).

The tools' mechanical, design-dependent offsets with respect to the machine coordinate system are $O_j$, $j = 1.2$, where $O_1 = 1441$ mm and $O_2 = 604$ mm. These offsets are taken into consideration by the harvesting controller when assigning detected asparagus stalks to the two harvesting tools. The harvesting process takes about 1 s, which means about 0.2 m of moving forward at the predefined machine traveling speed. Therefore, the harvesting controller assigns to each tool the closest asparagus, which is at least $x_T = 0.2$ m in front of the harvesting tool.

The harvesting process will be executed when

$$\mathrm{Enc}_C = x_{Wh} - x_T - O_j \quad (2)$$

where $\mathrm{Enc}_C$ is the current encoder value.

Due to the fact that the machine can move laterally on the dam due to its two castor wheels, drift in the $y$-direction can appear. In order to compensate those lateral drifts of the machine, the asparagus IDs are used to relate asparagus position updates to the asparagus already stored for harvesting in the PLC (harvesting controller). In this way, the harvesting tool can perform correcting lateral motion in order to increase the successful harvesting rate.

## III. Vision-Based Asparagus Recognition and Tracking

Fig. 2 shows an overview of the vision module inside the system architecture. It consists of three submodules: 1) point cloud generator; 2) camera calibration; and 3) online asparagus tracking.

The point cloud generator receives the RGB and depth images from the used RGBD camera and transforms them into point clouds [15]. The camera calibration module uses offline captured point cloud to calculate the transformation between the camera coordinate system $\{C\}$ and machine coordinate system $\{M\}$ as needed for the online asparagus tracking module.

### A. Point Cloud Generator

The RGBD camera provides both the color image, which has RGB values of each image pixel, and the depth image, which has the depth information of each pixel. A point in a 3-D environment has the position defined by $x$-, $y$-, and $z$-coordinate. For each pixel of the depth image, the camera estimates a distance value in real-time to the corresponding real-world object point. This distance is viewed as the $z$-coordinate of the corresponding point in the camera coordinate system, where the $z$-axis of the camera coordinate system is parallel to camera's view direction. The $x$- and $y$-coordinates are obtained following a method in [16]. The RGB values of the point can be obtained from the corresponding pixel in the color image. By combining all the information, 3-D-coordinates and color information, corresponding to the pixels of the depth image together, the point cloud is created.

### B. Camera Calibration

In order to enable reliable calculation of 3-D-position of each asparagus independently of the camera's orientation with respect to the machine coordinate system, a relation between the camera and the machine coordinate system must be obtained in advance. Therefore, the calibration procedure is carried out using the camera pose estimation technique.

In the work presented here, a template matching technique was used for the camera pose detection. For this purpose, two point clouds were considered, template point cloud (TPC) and model point cloud (MPC). TPC is obtained from the original point cloud of the machine frame, which is captured only once offline, by pruning it with the purpose of removing the moving parts such as ground and machine wheels as well as noisy outliers. In this way, the TPC contains only the machine frame as shown in Fig. 4 (red point cloud). MPC is the point cloud of the machine frame within the scene point cloud (SPC) captured online (gray point cloud in Fig. 4).

The pose estimation technique used here is an implementation of the iterative closest point (ICP) algorithm [15] available in the point cloud library (PCL) [17]. It was adopted to exploit the template matching technique and get the camera pose. The ICP

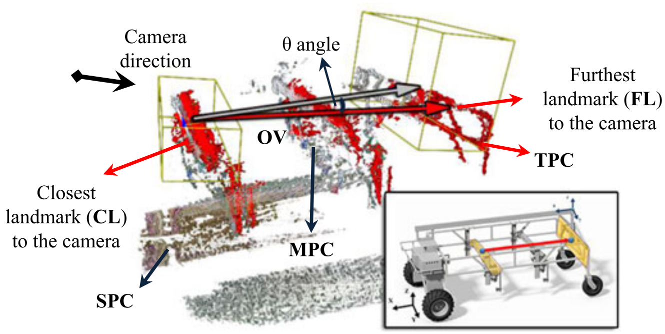


Fig. 4. Template point cloud (TPC) overlays the model point cloud (MPC) within the scene point cloud (SPC) after the translation of TPC to the location of MPC. Orientation vectors of TCP and MPC, as connecting the midpoints of two landmarks FL and CL, are illustrated, respectively, in red and gray (central image). The bottom right image represents the location of CL and FL in the real world machine frame.

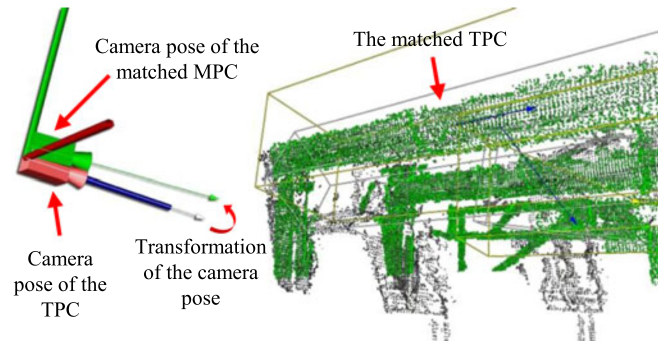


Fig. 5. Fully matched TPC defining the actual camera pose with respect to the machine coordinate system ${}^{M}_{C}T$.

algorithm is a standard solution to the alignment problems. It iteratively does three basic steps.

1) It pairs each point of the TPC with the closest point in the SPC.
2) It computes the transformation between the two considered point clouds which leads to the minimum Euclidean square error (ESE) value between the paired points.
3) It transforms the TPC and updates the ESE.

The convergence is done in term of the lowest ESE value which is below the certain threshold value. For the offline capturing of the TPC, the position of the camera with respect to machine frame is the same as during the online SPC capturing. However, the orientation of the camera might be different due to mechanical vibrations or camera re-assembling. Since only the camera orientation is changing and not the position, the TPC and MPC, which are within the SPC, are of the same scaling as important for the matching technique.

For a better convergence of the ICP algorithm and to avoid a blind search for the TPC in SPC, MPC and TPC should have a rough initial alignment. In this work, the initial alignment is based on detection of the two landmarks in both point clouds. The landmarks are defined as two horizontal parts of the machine frame, which are always visible in the camera view, one at the front and the other at the end of the machine frame. With respect to the camera view, one of the landmarks (at the front) is the closest landmark (CL) and the other one is the furthest landmark (FL) to the camera. Both CL and FL can be seen in Fig. 4 as surrounded by yellow bounding boxes. The detection of the aforementioned landmarks is done using the random sample consensus (RANSAC), a method which iteratively estimates parameters of a mathematical model (e.g., a linear structure) from a set of observed data points [18].

A novelty in the proposed approach is in the initial alignment of TPC and MPC using the detected landmarks to shorten the amount of time needed for the ICP algorithm to search for the best match. This approximate alignment is done by introducing the orientation vector (OV) as connecting the CL and FL midpoints (see Fig. 4). In fact, for both MPC and TPC, the respective OVs represent their orientation with respect to the camera coordinate system. OVs are later used to align MPC and TPC, which eventually leads to acquiring the camera calibration parameters.

The OVs of TPC and MPC are calculated both in camera coordinate system $\{C\}$ so that OV of TPC is calculated offline only once, whereas OV of MPC has to be computed online for all the frames captured by the camera.

The initial alignment of TPC with MPC using OVs consists of two steps: translation and rotation. First, TPC is translated over MPC (inside SPC) so that the starting point of its previously calculated OV coincides with the starting point of the OV of MPC, which is acquired in real-time (see Fig. 4). After such translation of TCP, two OVs compose the angle $\theta$ (see Fig. 4) with their starting points as its vertex. Second, the translated TPC must be rotated to overlap with MPC. For this purpose, the angle $\theta$ in the plane between two OVs must be zero degrees.

At this point, since MPC and TPC are initially aligned, the search space for the ICP algorithm to find the best matching position between MPC and TPC is minimized. Therefore, ICP can reach low values of ESE below a certain threshold and find the best matching alignment in a faster way than a blind search. The fully matched TPC is illustrated in green in Fig. 5. The camera pose which corresponds to the matched TPC is illustrated also in green, and it defines the actual camera pose with respect to machine coordinate system ${}^{M}_{C}T$. This results from the sequence of transformations (initial alignment translation and rotation followed by ICP transformation) of the camera pose of TPC (illustrated in red in Fig. 5).

### C. Online Asparagus Tracking

The asparagus tracking process is performed through two phases: asparagus detection in 3-D-point cloud and asparagus tracking in real-time. In the first phase, each asparagus stalk is detected in a single point cloud and corresponding features are extracted. Extracted features are used in the second phase to track the asparagus in subsequent frames. The output of the detection and tracking phase are the position vectors containing the coordinates of each tracked stalk in the camera coordinate system $\{C\}$. Multiplying obtained position vectors with the transformation matrix ${}^{M}_{C}T$ describing the camera pose in the machine coordinated system $\{M\}$, which resulted from the

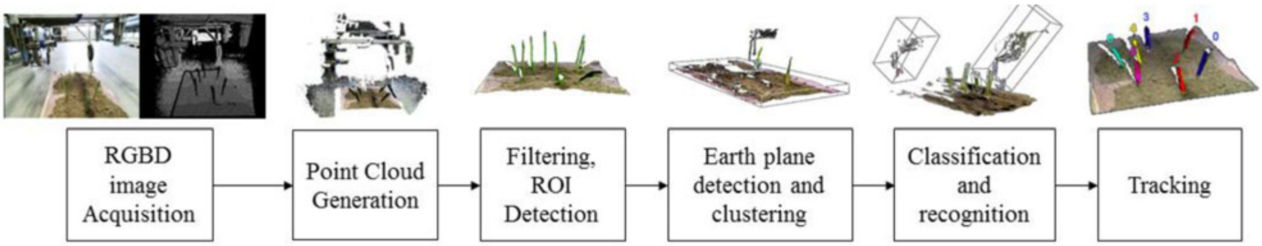


Fig. 6. Point cloud processing framework for asparagus detection and tracking.

above-explained calibration process, the asparagus position vectors in machine coordinate systems are obtained. These position vectors are then sent to the harvesting controller to accomplish the harvesting process.

The block-diagram of the 3-D point cloud-based asparagus recognition system, including point cloud generation step, is shown in Fig. 6. For the illustration of individual processing steps, the images of an asparagus dam created in a laboratory setting and captured by the RGBD camera mounted on the GARotics machine are used.

As obvious in Fig. 6, the point cloud contains the environment, the machine frame, the earth (at machine wheels' level) as well as the asparagus dam including the asparagus stalks. As only the point cloud of the asparagus dam, including the asparagus stalks, represents a point cloud part of interest, the first processing goal is to remove all points that are not of interest, that is, to detect the region of interest. For this purpose, in the work presented here, the pass-through filter of the PCL was used. This filter filters out some parts of a point cloud according to point coordinates. In the work presented here, all the points which are outside a volume estimated offline are filtered out. This offline volume estimation is done based on the facts that asparagus dam has to be inside the machine frame (between the wheels) and that the machine frame's height is known by construction. Starting from those facts, the coordinates of the points inside the estimated volume are calculated with respect to the machine coordinate system. Using the calibration matrix ${}^{M}_{C}T$, these coordinates are transformed into the camera coordinate system as the point cloud filtering is done with respect to the camera coordinate system.

As essential for the asparagus stalks detection, the filtered point cloud is further processed to detect the earth plane, i.e., to detect the dam's surface. To detect all the planes in a point cloud, the RANSAC plane segmentation method was applied. According to the distance threshold, the RANSAC method segments a group of points which belong to the same plane. The method also outputs the coefficients of the equation of the detected plane and the normal to the plane. The upper surface of the dam, also referred here as earth plane, is always in the view of the camera so that it appears in almost all the frames of the captured video. Therefore, the earth plane detection is based on the detection of all planes in 11 subsequent frames and on the tracking of the plane which appears in the majority of considered subsequent frames. The tracking is performed based on the extracted plane features such as normal to the plane. Once the earth plane is detected, it is removed from the point cloud so that finally only the points above the earth plane remained. The assumption is that the majority of those points belong to the asparagus stalks. In order to group the points which belong to particular asparagus stalk, a so-called clustering is performed. In the work presented here, the Euclidean clustering method was used, which can be viewed as a region growing algorithm. This algorithm first chooses a cluster seed point and then searches for the neighboring points of the seed point. If the neighboring point is within a distance tolerance, it will be considered as belonging to the cluster. Even though the majority of points above the earth plane, as said above, belong to the asparagus stalks, there can be other objects such as weed. Also, during the harvesting process, the points above the earth points which are clustered as belonging to a cluster could be points of the harvesting tool point cloud. Because of this, after extracting the cluster features, such as cluster's dimensions (height and width), the position of the cluster's centroid and cluster's orientation is extracted from each cluster that can be used for classification of clusters and final recognition of the asparagus stalks.

For the autonomous functioning of the harvesting machine, once the asparagus stalk is detected in the individual frame, it is necessary to track it in real-time from frame to frame of the video captured by the camera while the machine is driving over the asparagus dam. Besides, it is necessary to calculate the positions of the tracked asparagus stalk with respect to machine coordinate system, which is done using the calibration matrix ${}^{M}_{C}T$. Hence, the final output of the vision module, as explained in Section II-B, is vector $\{\mathrm{ID}_i,\ x_{Mi},\ y_{Mi},\ \mathrm{Enc}_i\}$. ID is assigned to asparagus $i$ during its tracking (for the sake of visualization, ID is a color in Fig. 6), and $x_{Mi}, y_{Mi}$ are coordinates of the asparagus $i$ in the machine coordinate system. $\mathrm{Enc}_i$ is the encoder value in the moment of detection of asparagus.

## IV. Harvesting Mechanics—Actuation and Tool

Selective harvesting in real open field conditions is aimed with the machine presented here. Hence, essential requirements to the mechanics have to be observed. The machine and the implemented mechanics were designed for different rough ambient conditions that have to be endured especially by the actuation, gearing parts, and guiding elements. Furthermore, the whole machine was designed in lightweight construction. Self-cleaning mechanisms in the gearing and tools were developed to enable a higher endurance and reliability in the work on the field. Due to the selectiveness in the harvesting process, the harvesting axis was designed to enable reaching of the detected stalk, located at a small distance to another stalk, without collateral damage.

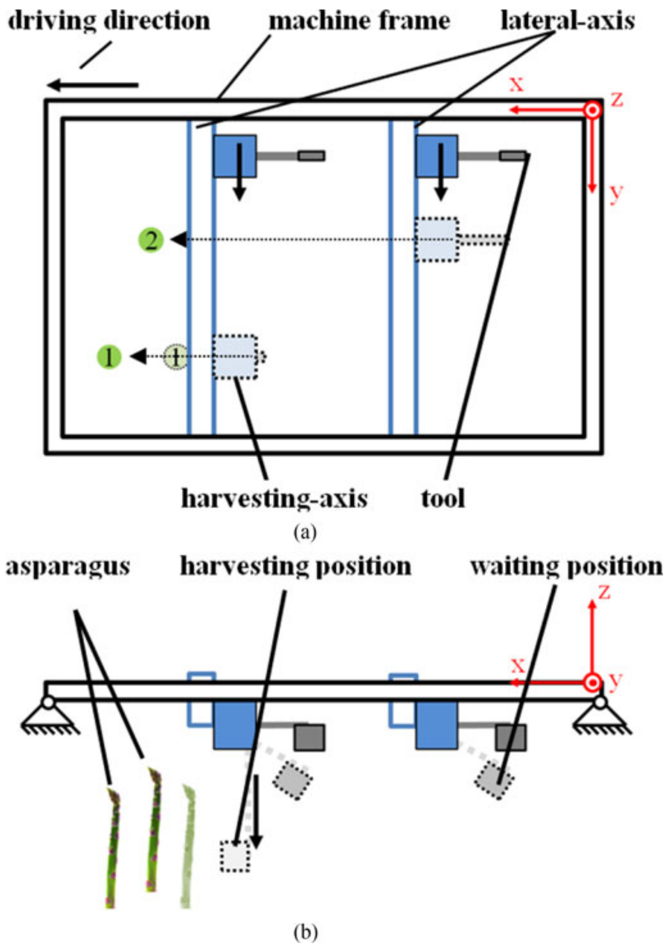


Fig. 7. Harvesting mechanics: (a) top view; and (b) side view.

According to these small distances, the harvesting tool was reduced in size. Furthermore, the claw design and the used gripping material enable a transmission of the arising forces while harvesting without damaging the stalks even under changed conditions such as the asparagus stalk diameter and the friction conditions. As the machine drives with the constant speed, forces caused by the relative motion of the stalks and the tool arise. Furthermore, to hold the asparagus after cutting, holding forces are transmitted on the asparagus. In addition, the realized tool enables even harvesting of a curved asparagus due to the claws design.

The harvesting mechanics enable motion of the harvesting tool to perform a harvesting of the detected asparagus. The mechanics of each tool are divided into two actuation mechanics: a lateral-axis for an adjustment transverse to the dam and a harvesting axis to perform a motion in growing direction of the asparagus (along the $z$-axis), as illustrated in Fig. 7. The end position for depositing the asparagus into a storage box is located at the side of the machine. As the asparagus damages itself as well as another asparagus by impacting vertical orientation into the box, the stalks need to be orientated horizontally during deposition.

In the harvesting process, according to the current harvesting strategy, the machine is driving along the dam continuously while tracking asparagus. If a stalk is detected, it is assigned to a tool that will proceed to waiting position. This waiting position in a lateral direction (along the $z$-axis) is the position of the detected stalk. Until the stalk is reached in driving direction, the tool is adjusted automatically transverse to the dam by the lateral axis, a compact belt driven linear unit, while tracking the stalk until harvest. Furthermore, the harvesting tool is held in waiting position, which means that the harvesting axis proceeds to a position closer to the dam while observing not to collide with another asparagus. When the start position for harvest is reached, the harvesting tool is set to harvesting position by the harvesting axis. The stalk is cut and grabbed and then horizontally put away on the side of the machine.

## A. Harvesting Tool

Two active harvesting tools are mounted on the harvesting axis. It is possible to increase the number of the tools to increase the productivity. In the prototype presented here, two tools were installed. The aim was to use only one actuation for each tool as it is more robust and lighter. The tool is actuated by a pneumatic cylinder which is suitable for the work under ambient conditions as it is sealed. The linear motion of the cylinder is transferred into a rotation by the leading element closing the claws to grab the asparagus. This mechanism is based on the principle of a spindle drive, but projected into a plane area and actuated in the opposite transmission direction—linear motion to rotation. Furthermore, closing of the claws leads to a cutting of the asparagus by two blades. These blades are mounted on the bottom of claws to cut the asparagus as low as possible for harvesting the asparagus stalk in full height. Afterward, to deposit the harvested asparagus, the claws can be opened actively again, Fig. 8(a). The tool has a width of 54 mm and a length of 450 mm. It is possible to open the claws, which are 90 mm in height, up to 50 mm.

As the harvesting tool, with its outer dimensions, influences the volume in which possible damage of close-by asparagus stalks could happen (so-called damage volume), it was designed as small as possible. Due to high accelerations and speed of the harvesting axis, as it influences the harvesting time and the damage volume, the harvesting tool should have a lightweight design. With this reduced mass and increased stiffness, a certain drive torque of the harvesting axis actuation leads to an increased acceleration as well as the forces on the tool and the gearing mechanism are reduced. Rubber bands were used as claws material to generate an equally holding force on the asparagus and not to damage the grabbed asparagus while harvesting. As the claws can be opened wide, a deviation between the real and the detected asparagus lateral position is tolerated.

While completely closing the tool, varying diameters of the asparagus (10–30 mm), different friction conditions, and a curvature of the stalks will not lead to unsuccessful harvesting. High accelerations for reaching the harvesting position are possible as well as for deposition of the grabbed asparagus.

A future version could be the development of a passive working tool. The basic idea is to use the continuous motion of the whole machine along the dam which leads to a relative motion

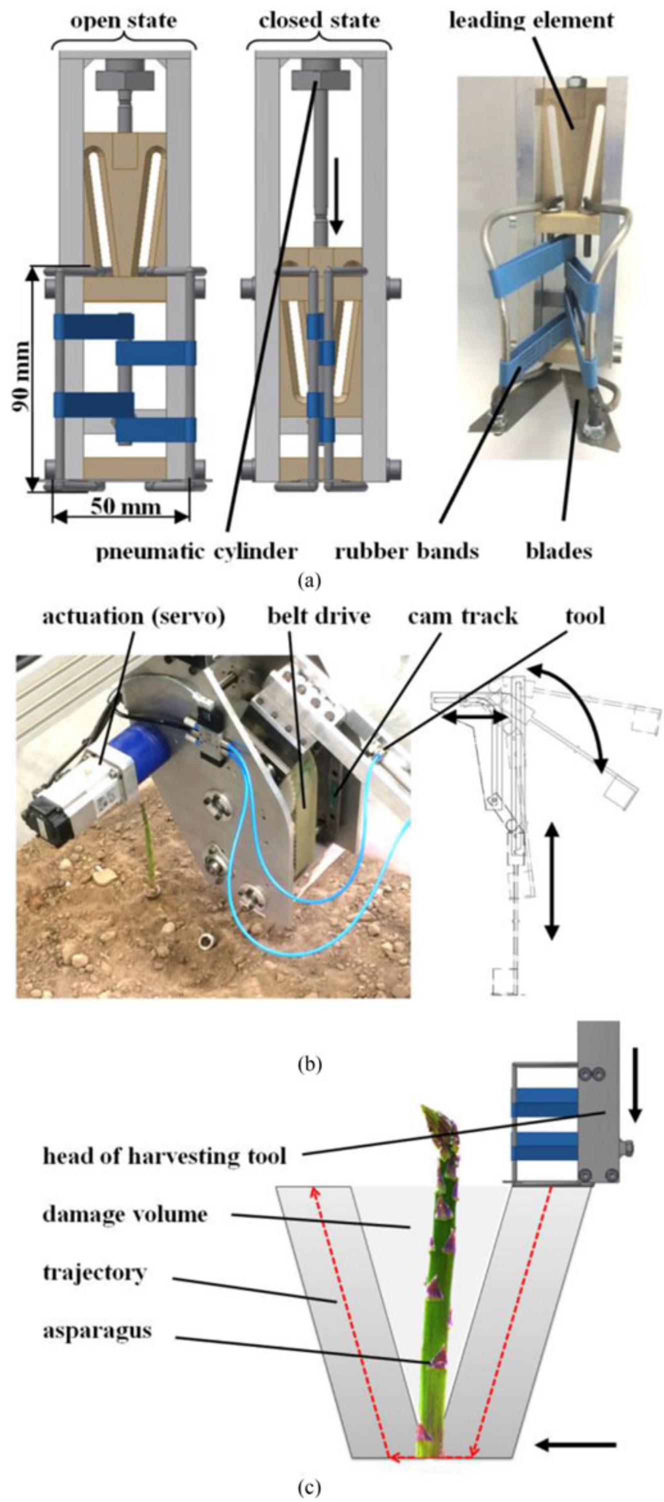


Fig. 8. (a) Lower part of the active harvesting tool. (b) Harvesting axis with one actuator (cam track) and mounted harvesting tool. (c) The trajectory of the harvesting tool.

between the asparagus stalks and the cutting blades respectively the claws. As the tool is positioned in lateral direction, the cutting and grabbing of the asparagus can be performed automatically without any additional actuation. For deposition of the stalks, the claws can be opened by moving against a stop plate using the motion of the harvesting axis. An important advantage of the passive concept would be the low complexity in design as well as in the actuation what makes the tool very robust. Furthermore, the lack of gearing parts and actuation reduces the mass which enables higher accelerations. The challenge of this idea is to deal with the variation of stalk diameters determining the grabbing force and the cutting point.

### B. Harvesting Axis

The harvesting axis influences the minimal distance between two stalks that can be harvested without damage of other stalks. As the machine is moving continuously forward while the harvesting tool is positioned by its harvesting axis, it is moving along the trajectory and it passes the related damage volume [see Fig. 8(c)]. This damage volume is reduced with higher accelerations of the harvesting axis and a change in the orientation of the harvesting tool with the implemented harvesting axis. Due to the implemented gearing and force transmissions as well due to the design, it resists the arising harvesting forces.

The harvesting axis on this machine is implemented by a servo actuated timing belt drive pulling the tool—mounted on the guide block—along a cam track. The cam track, a curved track rail with an L-shape, enables to transfer the rotation of the servo drive into a 90° clockwise swivel and then into a linear motion of the tool along the growing direction of the asparagus—and backward after cutting and grasping. This reduces the related damage volume, Fig. 8(b). Hereby, only one actuator is used for two motion directions which make the harvesting axis additionally more robust and easier to control. Furthermore, less energy is needed which is an advantage due to the use of batteries as a power supply. For a higher robustness, the guiding elements are sealed from ambient conditions.

## V. Performance Evaluation—Field Tests

The first open field tests were conducted to evaluate the performance of the presented prototype robotic harvesting system. The field tests were performed on the asparagus fields of the GARotics project partner C. Write & Son Ltd. in Lincolnshire, U.K. For the purpose of conducted outdoor field tests, the harvesting machine was appropriately covered so to provide rain protection. A photo of the machine driving over the asparagus dam is shown in Fig. 9(a). An illustration of the asparagus harvesting scene as seen by the camera of the system is shown in Fig. 9(b). Fig. 10 illustrates a part of the harvesting process of one asparagus stalk.

Prior to the shown harvesting, the asparagus stalk was detected by the vision module and classified as being longer than 15 cm. The features vectors of these detected asparagus stalks were sent to the PLC (harvesting controller) for initiating the harvesting process. The PLC decided, based on the status of the tools (whether the tool is engaged already in the harvesting process or not) and the location of the asparagus, that the first tool should perform the harvesting.

Asparagus stalks that were close to each other could be reliably detected by the vision module if they were at least 2 cm away from each other. Otherwise, the Euclidean

(a)

(b)

Fig. 9. (a) Robotic harvester driving over an asparagus dam. The asparagus process is seen by the camera. (b) The storage box on the side of the machine.

Fig. 10. Illustration of a part of the harvesting process, asparagus stalk approaching and grabbing by one of the harvesting tools.

clustering during asparagus detection grouped the stalks together. However, the limitation introduced by the harvesting tool in order to successfully perform selective harvesting was that the stalks should be at least 6 cm away from each other in the $y$-direction and at least 10 cm in the $x$-direction. If these conditions were not met, the neighboring stalks could be damaged during harvesting. Also, sometimes two stalks were harvested together, though without damaging. An estimate in performed experiments was that 10–15% of the stalks were that close together.

## VI. Discussion

The performed initial field tests demonstrated the applicability of the presented robotic harvester for the effective selective harvesting of the green asparagus. Those tests also indicated the necessary improvements to be done on the system in future work. As first, the harvesting of two stalks together, which are close to each other, could be avoided by decreasing the vehicle speed, increasing the velocity of the harvesting tool in the $z$-direction, as well as by reducing the size of the gripper.

The average velocity of the asparagus harvesting machine was 0.2 m/s. An average mechanical harvesting cycle took about two seconds, which means that once a harvesting process started, the tool was blocked for at least 0.4 m. This means that having two tools, an average of five asparagus plants/meter could be harvested. If the asparagus density on the field was higher, the machine had to harvest the same dam several times. In terms of reliability, our field tests have shown that in about 90% of the cases, the harvesting process was successful, meaning that the gripper successfully grasped an asparagus and deposited it in the storage box placed on the side. A different solution of bringing the harvested stalks into the storage box could also contribute to optimization of the harvesting process.

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**Adrian Leu** received the Ph.D. degree in computer vision and robotics from the University of Bremen, Bremen, Germany, in 2014.

He was a Technical Manager for the EU FP7 project CORBYS, responsible for the development and implementation of the cognitive robot control architecture and system integration. Currently, he is a Postdoctoral Research Fellow with the University of Bremen. His research interests include advanced human–robot interaction, computer vision, control architectures, and system integration.

**Mohammad Razavi** received the M.Sc. degree in media informatics from the University of Bremen, Bremen, Germany, in 2015.

He collaborated with the Fraunhofer MEVIS Institute, Bremen, for several projects in medical imaging and development of computer-aided design systems. He was also a Research Associate with the Institute of Automation, University of Bremen, developing robot vision and machine learning algorithms for automated agricultural robots. His research interests include machine learning, computer vision, and image processing.

**Lasse Langstädtler** received the M.Sc. degree in production engineering from the University of Bremen, Bremen, Germany, in 2014.

Since then, he has been a Research Assistant with the Bremen Institute for Mechanical Engineering, Bremen. He collaborated on several industrial projects as a Development Engineer responsible for the concept and design of production machines and mechanical parts such as the harvesting tool of the harvesting machine for the GARotics project.

**Danijela Ristić-Durrant** received the M.Sc. degree in automatic control and robotics from the Faculty of Mechanical Engineering, University of Niš, Niš, Serbia, in 1998, and the Ph.D. degree in electrical engineering from the University of Bremen, Bremen, Germany, in 2007.

She is with the University of Bremen, as a Postdoctoral Researcher and Lecturer. Since July 2016, she has also held the title of an Associate Professor of automatic control and robotics with the Faculty of Mechanical Engineering, University of Niš. She was a Researcher and a Project Manager for the FP7 EU-funded project CORBYS-Cognitive Control Framework for Robotic Systems, and the Coordinator of several bilateral projects in the field of rehabilitation robotics and robot vision. She has co-authored one university book, one book chapter, and numerous journals and conference articles. Her current research interests include rehabilitation and assistive robotics, and sensor-based control of robots.

**Holger Raffel** received the Ph.D. degree in electrical engineering from the University of Bremen, Bremen, Germany, in 2004.

From 1996 to 2006, he worked on several research and development projects in close cooperation with a large number of industrial companies. For 10 years, he has been leading the Bremen Center of Mechatronics (BCM), Bremen, as the General Manager. For many projects, he founded expert networks as the basis for application-oriented research and development. He coordinates project partners from regional and European companies and finds synergetic effects, which result from the cooperation with the industry. BCM offers support by carrying out research projects, and arranging events for further training and education in cooperation with the companies.

**Christian Schenck** received the Ph.D. degree in mechanical engineering from the University of Bremen, Bremen, Germany, in 2008.

Since then, he has been a Chief Engineer with the Bremen Institute for Mechanical Engineering, University of Bremen, and is the Head of the division mechatronics.

**Axel Gräser** (M'97) received the diploma in electrical engineering from the University of Karlsruhe, Karlsruhe, Germany, in 1976, and the Ph.D. degree in control theory from the TH Darmstadt, Darmstadt, Germany, in 1982.

He was the Head of the Control and Software Department, Lippke GmbH, Germany, from 1982 to 1990. From 1990 to 1994, he was a Professor of control systems, process automation, and real-time systems with the University of Applied Sciences, Koblenz, Germany. Since 1994, he has been the Director of the Institute of Automation, University of Bremen, Bremen. He was also a Foreign Advisory Professor at the Korean Advanced Institute of Science and Technology, Daejeon, Republic of Korea, and an Honorary Professor at the Polytechnic University of Timisoara, Romania. He has been coordinating more than 20 national and international projects in process automation, control, and rehabilitation, among them four EU grants: BrainRobot, BRAIN, IntARWeld, and CORBYS.

**Bernd Kuhfuss** received the Ph.D. degree in mechanical engineering from Hannover University, Hannover, Germany, in 1983.

From 1984 to 2000, he held positions as a Research and Development Manager and a Managing Director in leading German machine tool companies. Since 2000, he has been a Professor of machine tools with the University of Bremen, Bremen, Germany. In 2008, he founded the Bremen Institute for Mechanical Engineering, Bremen University.