



HAL
open science

Development of autonomous robotic platforms for sugar beet crop phenotyping using artificial vision

B. Benet, C. Dubos, F. Maupas, G. Malatesta, R. Lenain

► To cite this version:

B. Benet, C. Dubos, F. Maupas, G. Malatesta, R. Lenain. Development of autonomous robotic platforms for sugar beet crop phenotyping using artificial vision. AGENG Conference 2018, Jul 2018, Wageningen, Netherlands. 8 p. hal-02155159

HAL Id: hal-02155159

<https://hal.science/hal-02155159v1>

Submitted on 13 Jun 2019

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Development of autonomous robotic platforms for sugar beet crop phenotyping using artificial vision

Bernard Benet ^{a,*}, Camille Dubos ^a, Fabienne Maupas ^b, Ghislain Malatesta ^b, Roland Lenain ^a

^a IRSTEA, UR TSCF, 9 avenue Blaise Pascal, 63178 Aubière, France

^b ITB, 45 rue de Naples, 75008 Paris, France

* Corresponding author. Email: bernard.benet@irstea.fr

Abstract

Phenotyping is a major challenge in international agronomic competition. In a perspective of modern and sustainable agriculture, understanding the relationship between genotype and phenotype according to the environment is one of the major projects of agronomic research. Artificial vision devices embedded on robotic platforms, working in visible or hyperspectral color fields permit to carry out many geometric and colorimetric measurements on crops. From this information, operations like crop varieties comparisons and disease detection are realized. For sugar beet crops, phenotyping operations are made from a two small leaf stage up to the final stage just before harvesting task. Two robotic devices were used to make colorimetric and geometrical measurements on sugar beet plants. An autonomous mobile robot navigating in crop lines for little growth stages, embedded two cameras. A first one, with an oblique orientation permitted to realize autonomous crop row tracking and the second one in a vertical position was used to record cartographic images and make detailed measurements on sugar beet plants. The second robotic platform was a manipulator arm with 6 degrees of freedom, fixed on a mobile linear axis to make measurements for advanced growing stages. Active perception operations realized with the embedded camera fixed at its extremity, consisted in locating by artificial vision the plant leaves in 3D environment and from this information, the camera was automatically positioned at various desired heights and orientations for each detected leaf, for carrying out, with accuracy, image acquisitions and measurements. Experimentations realized with both robotic platforms, for various sugar beet growing stages, shown the interest of these devices for following and analyzing in detail the geometric and colorimetric evolution of sugar beet plants in the fields, in order to carry out some phenotyping measurements and particularly for detecting some diseases.

Keywords: Mobile robot, vision, active perception, manipulator arm, phenotyping

1. Introduction

In recent years, the use of new technologies has become widespread in agriculture, through precision farming, with the aim of improving agricultural operations. The evolution of increasingly sophisticated perception sensors has enabled the development of high performance autonomous navigation systems, which can in particular perform agricultural tasks of crop monitoring, and measurements for different types of plants, while limiting human intervention, relatively restrictive. An important point of growing interest for the agricultural community is the protection of crops against a variety of factors that lead to reduced yields, such as diseases, that can affect plants during the growth process. Agriculture has become much more than just a way to feed ever-growing populations. Indeed, plants have become an important source of energy, and are a fundamental piece in the puzzle to solve the problem of global warming. There are several diseases that affect plants with the potential to cause devastating economic, social and ecological losses. In this context, diagnosing diseases in an accurate and quick way is of utmost importance. There are several ways to detect plant pathologies. Vision devices are currently used to detect some diseases, which can be seen in the visible or invisible lighting spectrum. So, it is necessary to work with RGB cameras and also with hyperspectral devices to develop image processing tools for disease detection. A large amount of information on the subject can be found in the papers by (Bock et al., 2010), (Mahlein et al., 2012) and (Sankaran et al., 2010). Fungal diseases have recently led to losses in world production, especially for sugar beet, wheat or maize. Also, in (Sharr et al., 2016), we find a comparison of leaf detection algorithms presented at the Leaf Segmentation Challenge in 2014. Article in (Barbedo et al., 2013) contains a state of the art of disease detection from different types of sensors (RGB, thermal, hyperspectral ...). The improvement of disease detection by automatic objective tools, which could replace tedious and imperfect human visual detection, has therefore become a major concern for agricultural producers. Reliable disease detection methods at the microscopic scale are also used (Henson et al., 1993) and (Hobbs et al., 1987), but are destructive because they require samples of plants. There is therefore a need for new innovative techniques to detect diseases as quickly as possible in crops, to prevent the spread of these diseases over large areas. The implementation of sensors technologies and algorithms for automatic phenotyping are of increasing importance. Sensors such as 3D Time-of-Flight cameras can be used for phenotyping under outdoor conditions (Kloze et al, 2011) and (Paulus et al, 2014). The influences of direct light, speed, humidity and dust on the measurements of the characteristics of the cameras and color dependence, noise level and depth resolution were analyzed by the application of phenotyping.

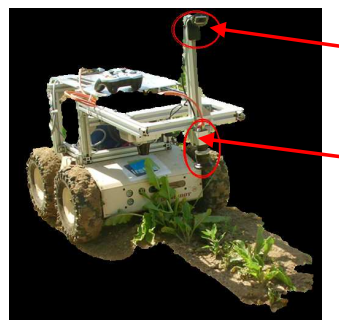
The benefit of analyzing the information is the ability to develop strategies to optimize the quality of their processing, e.g. next to spectral information on these important phenotyping methods is the exact measurement of the plant's morphological characteristics, for example, leaf size, leaf configuration, angle of the tree, plant height or stem thickness. In this paper, we will focus on the development of phenotyping tools and techniques to realize automatically by artificial vision, geometric and colorimetric measurements on sugar beet plants. In this application, we will be interested in two phenotyping platforms, to work on different stages of plant growth. On the one hand, a mobile robot carrying two vision systems to navigate crops for low lift stages and perform different measurements, and on the other hand, a mobile manipulator was carrying a camera for high growth stages. With regard to this second platform, the objective is to develop an autonomous robotic system allowing the camera to be placed at the desired location with respect to the plants, by means of active perception techniques. Its goal is to realize precise image acquisitions, in order to detect and identify leaf diseases, which usually appear when the plants have reached an advanced stage of maturity, and to quantify the diseased surfaces. During the first year of this project, a feasibility study, related to the development of a robotic system intended to perform measurements by artificial vision for the detection of diseases on beet leaves and the study of their propagation in crops, was carried out. This study led to the choice of the robotic system named BettyBot chosen for phenotyping operations and particularly for disease detection on sugar beet plants.

2. Materials and Methods

Two robotic platforms were used for phenotyping operations: a light mobile robot for low level stages and a big one composed of a linear axis and a manipulator arm, for high level stages.

2.1 Mobile robot

For little vegetation stages, a light mobile robot (weight: 30 kg, length: 50 cm, width: 30 cm) was used (Figure 1). This one embedded two cameras to carry out two operations: a Webcam and a GigaEthernet device. The first one, in an oblique position, permits to achieve a crop row tracking by visualizing three beet lines and the second one realizes image acquisitions on the central line to obtain a cartographic image and make measures for phenotyping operations. Both operations were achieved in parallel and in real time. Image processing algorithms were developed in order to autonomously follow the crop lines, realize measurements and record images of the central line. At the end of the navigation, the 2D cartography of the central line was obtained. From this one, geometric and colorimetric information were obtained (beet counting, spacing between plants, leaf area, level of red, green and medium blue, presence of black areas in the leaves, ...).



Webcam camera
Resolution: 1280 x 720

GigaEthernet camera
Resolution: 2044 x 2044

Figure 1 - Mobile robot with both embedded cameras

Various robotic platforms carrying vision systems to perform various agricultural operations have been developed, for phenotyping operations, as example (Subramanian et al., 2012) and (Gustavo et al., 2012). (Åstrand and Baerveldt, 2012) have developed a robotic platform, similar to our platform, with the use of two vision devices for weed control on sugar beet crop lines, one for crop row tracking and the other for detection and measurements on crops. Different methods are used for vision tracking by detecting the vanishing point (Ding et al., 2014) or (Kong et al., 2013). The intuitive idea is to make an assumption about the relative position between the vehicle and the crop lines that must be corrected by observing the image. With the development of precision agriculture, a lot of work has been done in order to be able to use assistance robots (assistance to the driving of agricultural machines) or even autonomous ones. For this purpose, it is necessary to be able to follow cultures in a precise way. Concerning the use of a camera for those crop row tracking, different approaches are used. Hough method is often applied on images to find crop lines, after applying thresholding and morphological operations, such as (Rovira-Mas et al., 2005) or (Montalvo et al., 2012). An interesting way of determining the position and orientation of crop lines in the image is outlined in (Gee et al., 2008). The author starts from a wide view of the rows (at least 6 visible) that segment from the function of excess of green, and applied two successive Hough methods to finally obtain the vanishing point and the width of the rows. One way to detect crop lines when many weeds are present is also exposed in the literature. To that end, two thresholding operations are used. The first one permit to isolate plants and the second one is applied to distinguish the plants from the weeds.

Finally, to find the culture lines, a linear regression is made around the average position of the rows. This method is certainly very powerful, but the model used imposes that the variations of position of the lines in the image is weak. Given the requirements of the specifications and a priori knowledge of the environment, a bottom-up approach seems to be preferred. Indeed, there are two general principles for a procedural approach: the so-called top-down approach and the bottom-up approach. In the first case, we start from a large amount of data that must be broken down and sorted in order to obtain a result. In the second case, we try to confirm a hypothesis thanks to the data of the sensors (which requires information on the environment in which the system evolves).

In our application, for crop row tracking with mobile robot, a geometric model of the robot has been defined, taking into account the position of the Webcam on the robot as well as the geometry of the ground and the spacing between the beet lines (Figure 2), to achieve a line tracking task with the Webcam, which was positioned so that it could visualize the vanishing point of the crop lines on the images.

Geometric parameters of the robot model

- X_0 lateral deviation of the robot from the central line
- Y_0 the distance from the robot's center to the camera following the direction of robot moving
- Z_0 the height of the camera relative to the center of the robot
- α yaw angle
- β pitch angle
- γ angle of the camera relative to the plane of robot moving

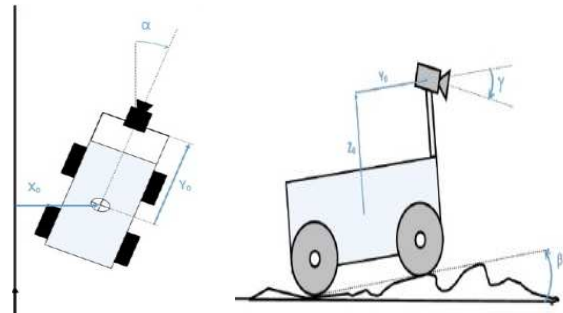


Figure 2 - Mobile robot geometric model for crop row tracking

The technique used in this application is to define restricted search areas, from the knowledge of the environment, in which the objects to be detected (beet leaves) must be located. One of the major interests of these methods is to reduce the computation time by only looking at interesting parts of the image while ensuring a result consistent with reality. To be able to find the lines of culture, one estimates at first (from the knowledge a priori) the state of the mobile robot, in real time. Then, the lines around their estimated position are searched for the current state of the system. To carry out these operations, a model of the robot with the camera, in the given environment, must be developed. The complete image processing method is the following: first, the original image is thresholded and binarized, using image processing algorithms such as color classification and mathematical morphology operations (OpenCV functions), to detect beet leaves. Then, the image is divided into different horizontal and vertical zones (3 columns corresponding to three crop lines, in which the gravity centers of each leaf are searched). A linear regression operation allows obtaining sugar beet rows for the three lines. From this information, the application of a Kalman filtering makes it possible to automatically define and limit the search zones of the three beet lines, during the successive searches of beet leaves on the images acquired by the camera (Figure 3). Finally, visual control operations are applied for the crop row autonomous tracking task.

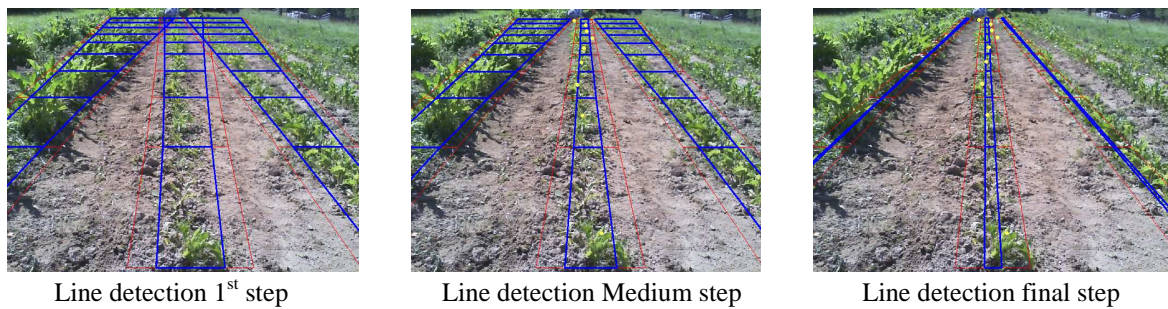


Figure 3 – Detection of crop lines using Kalman filtering

2.2 Bettybot Robot

Figure 4 below shows Bettybot robot in a laboratory with a camera at its extremity, which will be used for phenotyping measurements for advanced level stages. It included a motorized linear axis, on which a manipulator arm with six degrees of freedom is mounted/ fixed (UR5 Universal Robot model). At the end of this arm, a vision sensor such as a color camera or a hyperspectral camera was embedded to collect/take images on sugar beet crops, with the possibility to acquire images with various desired heights and orientations. Figure 5 presents this robot embedded on a tractor for the application in the fields.



Figure 4 - Bettybot robot with GigaEthernet camera

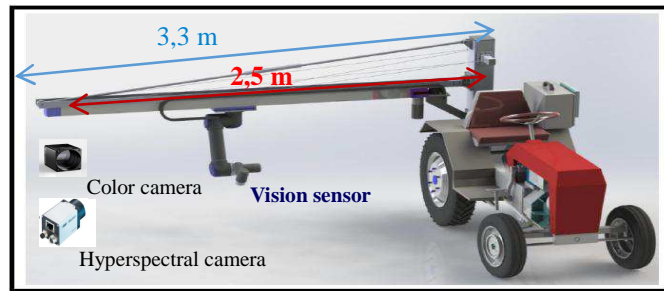


Figure 5 - Bettybot embedded on a tractor

The general application with this robotic platform is shown in Figure 6. The tractor navigates outside the crop lines and stops when the linear axis is aligned with a crop line. Then, the mobility of linear axis and manipulator arm permit to acquire and compute images on lengths of beet line of about 3m.

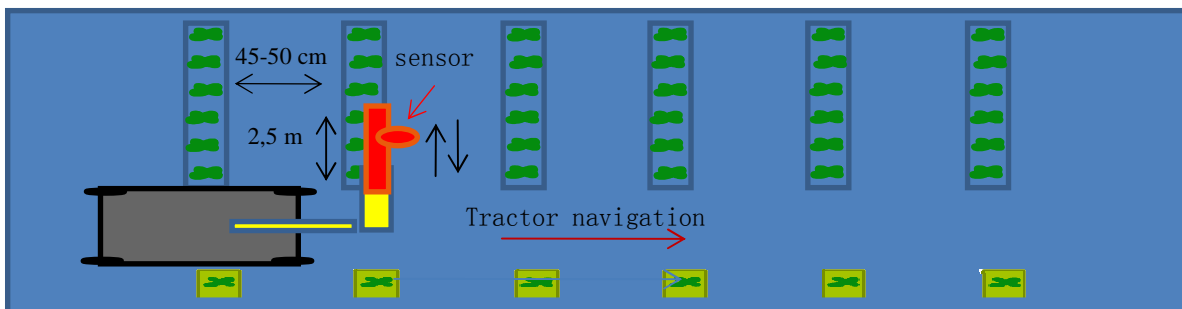


Figure 6 – General operations in sugar beet crop lines

The use of such a system makes it possible to observe the beet leaves according to different points of view, thanks to the complementarity between the manipulator arm and the linear axis, which enables the sensor to reach a large number of positions and orientations in relation to the leaves and to be able to work on different plants. However this association causes difficulties in the control. Indeed, this system is redundant, that is to say it has more control variables (degrees of freedom) than sensor position data. Here, our system has seven joints, so seven variables of commands on which one can act, to place the sensor to a pose (position and orientation) defined by 6 values (3 for the position and 3 for the orientation). There are infinite configurations of the system to place the sensor in a desired pose. Control/command algorithms have been developed for this operation, by acting on the six degrees of freedom of the UR5 arm and taking into account the problems of redundancy. The interest of the phenotyping platform is that its behavior adapts according to the perception of the state of the vegetation. Thus, the movements of the system must be enslaved from observation algorithms of beet plants, to ensure the most accurate detection as possible. It is also necessary to take into account the specificities related to the evolution in natural environments in these controls, such as the variation of the brightness, to adapt the behavior of the robot. The main task is to detect the beet leaves and then observe them using the sensor located at the end of the manipulator arm, in order to detect diseases. This task can be broken down into different functions: the first will be to detect the different leaves to be observed, then to place the sensor close enough above them, and finally to move around to determine the angle of view allowing obtaining the maximum relevant information for the detection of diseases. The work done so far is focused on two areas: perception, through crop detection, and control, including, among other things, the management of system redundancy.

2.3 Sugar beet leaf detection

A pixel color classification in RGB color space, using SVM method, was made, in order to discriminate both pixel types (sugar beet leaf and ground pixel) (Figure 7), considering different ground colors and beet leaves corresponding to various level stages (various green colors).

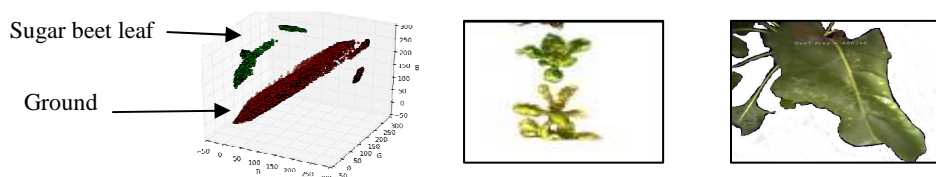


Figure 7 – Color discrimination between sugar beet leaf / ground points using SVM classification

3. Results and Discussion

3.1 Crop row tracking result

Figure 8 shows an example of a result obtained from monitoring beet line detection, with Webcam camera with the three steps of the developed algorithm: in (a) thresholding operations with the application of SVM classification and morphological operations to detect sugar beet crops and remove noise, in (b) the gravity centers of leaves in each defined rectangular area are obtained, and in (c) an example of final result obtained is presented, with the use of a Kalman filtering operation for improving the crop line detection. From this information and taking into account the position and orientation data of the camera embedded on the robot, the lateral deviation between the robot and the central line was obtained. Then a referenced vision command was applied for autonomous robot navigation.

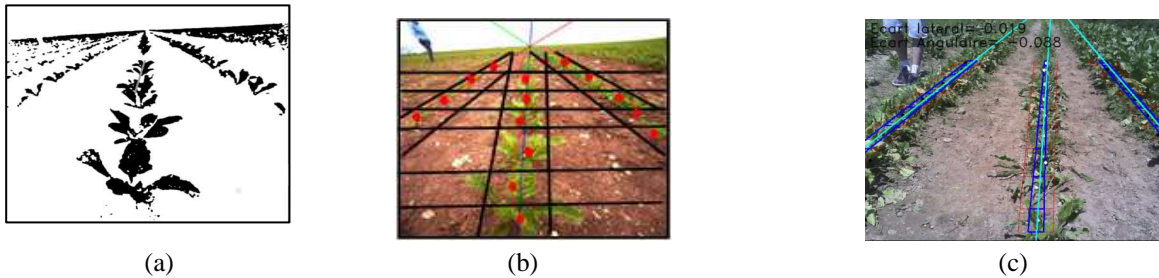


Figure 8 – Sugar beet line detection with Webcam camera

3.2 2D mapping of beet crop lines

With the GigaEthernet camera, the objective was to acquire images on the central line, to obtain, after image processing, a cartographic image. From this cartographic image, geometric measurements can be made, such as the counting of plants and leaves, the spacing between the plants, the leaf area, but also colorimetric measurements, allowing to analyze in detail the colorimetric variations. on the different leaves (Figure 9).



Figure 9 - Cartographic image of a sugar beet line obtained with GigaEthernet camera

From this 2D mapping, geometric and colorimetric measurements were carried out, such as beet plant counting, leaf area of each plant, distance between plant, mean color in RGB or in HSV color space, in order to analyze the color difference between leaves, to detect some disease and to see the growing level of the culture. Also, data obtained with these cartographic images, at different time during the growing evolution, permit to make comparisons between crop varieties and also between fields.

3-3 Detection and localization of beet leaves with Bettybot robot

An image processing job has been performed. The objective was to detect the beet leaves of a potted plant in a global manner and to achieve measures on this set of pixels belonging to the beet leaves, such as the position of the gravity center and total leaf area (Figure 10). From these image data, control/command operations of UR5 manipulator arm was performed. The goal was to use the image data to position the robot extremity above a plant.



Figure 10 - Detection of sugar beet leaves by image processing

The desired pose of the sensor is estimated according to the sensor data. First, an image processing algorithm extracts the green areas of the observed image (by thresholding and morphology) then retrieves the different information that is the position of the barycenter of this area in the image and its size in pixels, as shown in the previous figure. The goal is to superimpose the center of gravity of this area with the center of the image. For that, one calculates the displacement to be carried out in the camera frame, for the moment simply by displacing the sensor in a plane parallel to the ground, then one expresses this displacement in the global coordinate system. The presented works, in this paper are based directly on the works of (Spong et al., 2001) and (Craig, 2005). The objective of this project is to detect beet leaves and then observe them using the sensor located at the end of the manipulator arm in order to detect diseases. This objective can be broken down into different tasks: the first will be to detect the different leaves to be observed, then to position themselves at the top close enough, then to move around to determine the angle of view allowing obtaining the maximum of relevant information for the detection of diseases. At first, the work done so far has been to move the camera attached to the manipulator arm above a plant. The position of the desired effector is then obtained. A performance criterion must be defined to reduce the possibilities. There are articles on trajectory generation and control mobile manipulators based on the value of manipulability. This criterion was defined in (Yoshikawa, 1984) and represents the ability of a manipulator robot to modify the pose of its effector in all directions. It is used in (Yamamoto and Yun, 1992) to determine the joint coordinates of the manipulator arm corresponding to maximum manipulability, these coordinates being subsequently fixed and only the mobile platform moves to follow the trajectory. In (Bayle et al., 2003), the theory developed in (Yamamoto and Yun, 1992) has been extended to all mobile manipulators. Thus, this criterion defines the whole system, and makes it possible to generate, from kinematic models, coordinated movements of the whole system. More recently, this criterion has been optimized for manipulator arms with six degrees of freedom (Zang et al., 2016). There are also different ways to formulate the problem of control of mobile manipulators. In (Soetanto et al., 2003), three formulations are listed: the achievement of a desired pose by the terminal organ, path tracking or trajectory tracking. Finally, a second aspect that may be interesting to dig is the definition of an image quality metric. Indeed, the purpose of the system is to enable detection of diseases, which implies obtaining images of sufficiently good quality. The criteria for image resolution and sharpness are to be taken into account. Moreover, as the system must be used outdoors, it will be subject to variations in brightness, but also to glare due to the sun or the movement of leaves.

3-4 Mobility control of Bettybot robot

Once the installation of the desired effector is estimated, the system is set in motion according to a control law which has been developed to manage the redundancy of the system. To control the robot, we then base ourselves on optimizing the working space of the manipulator arm. The ultimate goal is to come to observe leaves according to different points of view, it is necessary that the orientation of the camera can be modified. Therefore, the working space of the manipulator arm should be as large as possible, when the camera is centered over a plant, to allow this change of orientation. To do this, we base ourselves on the distance between the desired position of the camera and the limits of the working space of the manipulator arm (Figure 11). If this position is inside the working space of the manipulator arm, only the latter is set in motion. On the other hand, if the position to be reached is too far away, the support translate to center the working space of the manipulator arm above the plant to be observed, ie in order to center the base of the manipulator arm to the maximum above the plant. In practice, a coefficient λ is defined as a function of the distance between the desired position of the sensor and the limits of the working space of the manipulator arm, along an axis parallel to that of the linear axis. Its values are in the range $[-1; 1]$ so that when the desired pose of the sensor is close to the center of the working space, λ is zero and, in this case, only the manipulator arm is set in motion. On the other hand, if the desired pose is outside the working space, or close to the limit, then $\lambda = \pm 1$ (the sign differs according to the direction of the displacement to be performed), and the Linear axis only moves in order to center the base of the manipulator arm above the plant. If the plant to be observed is between the two previous cases, then the manipulator arm and the linear axis move in a coordinated way. Once this coefficient λ is determined, two commands are sent: one for the linear axis which is proportional to λ , and one second for the manipulator arm joints, which is inversely proportional to λ .



a) Plant inside the working space of the arm



b) Plant outside the working space of the arm

Figure 11 - Influence of the space between the desired position for the camera and the working space of manipulator arm

In Figure (a), it may be noted that the plant is located almost under the base of the manipulator arm, fixed on the support in translation. In this case, the arm alone can be positioned above the plant, while keeping sufficient freedom of movement to allow the change of orientation of the camera. In contrast, in Figure (b), the plant being too far from the base of the manipulator arm, the translation of the support is then necessary to allow a change of orientation once the camera centered above the plant. The previously discussed command approach has been tested on the actual system. The following curves in (figure 12) represent the evolution of three elements: the lambda coefficient, the linear axis speed and the respective speeds of each of manipulator arm joints as a time function. The left column of each element shows the behavior of the system in the case where the plant to be observed is in the working space of the manipulator arm (Figure 11, case a), while the right one represents the case where the plant is located at outside the workspace (Figure 11, case b).

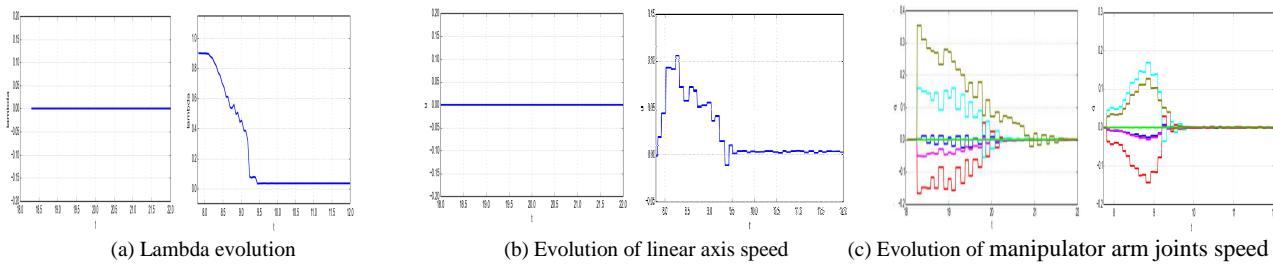


Figure 12 – Experimental results with Bettybot Robot

In the first case, as the desired pose of the sensor is located in the working space, the coefficient λ is zero and only the manipulator arm is moving. Indeed, the speed of the linear axis is zero in this case, while the articular velocities of the manipulator arm evolve as a function of time, until becoming zero when the sensor is centered above the plant. In the second case, the desired pose of the sensor is located at the limit of the workspace. The value of λ is then almost equal to 1 and the speed on the linear axis is therefore non-zero. It is also observed that the evolution of the speed of the axis follows the evolution of λ , it increases initially until reaching the maximum speed, then decreases at the same time as λ , which corresponds to the relationship of proportionality between the two sizes. During this time, the articular velocities are rather weak at the beginning, as λ is large, then increase as λ decreases, and become null when the sensor is above the plant. The developed algorithm for mobility and control of Bettybot robot, in order to move the camera at a desired position from a sugar beet crop position is satisfying. It makes it possible to weight the displacement of the linear axis and the manipulator arm as a function of the working space of the manipulator arm and permit to optimize this space in order to execute observation trajectories around the leaves. In addition, the calculation of the coefficient between the two commands can be parameterized according to the desired behavior: it is possible to give more weight to the movement of the manipulator arm, or, on the contrary, to promote the displacement of the linear axis.

4. Conclusions

In 2017, the robotic platform Bettybot was taken in hand, by looking at different aspects in the field of robotics, to meet the needs of the Phénaufol project: mobility of the linear axis and the arm UR5, perception with the using of a color camera, attached to the end of the manipulator arm, control / command operations, working on the one hand in open loop, by sending commands on the 7 degrees of freedom of Bettybot, to position the color camera at the desired locations to make acquisitions and image processing, and secondly in closed loop, to automatically control the 7 degrees of freedom, from the image data obtained, in real time, by image processing. Acquisition and image processing work was also carried out for early growth stages, with the Jaguar mobile robot, in order to obtain map images of beetroot lines and to perform geometric and colorimetric measurements.

Next experimentations realized in laboratory and in the fields, will consist to apply and optimize the developed methods about perception by vision and control/command of Bettybot robot, working on several aligned sugar beet crops, at high growing stage, taking into account the redundancies of the seven degrees of freedom for robot control, and the lighting variations in the fields which can affect the sugar beet leaves detection. Concerning artificial vision, one important work will consist in the detection of each plant independently, using new image processing methods and for each plant, the aim will be to detect its leaves and to obtain some geometric data such as gravity center and the position of the central vein. Therefore, this will allow coming to observe the plant leaves one by one, and to test different observation trajectories. It will also be possible to integrate the calculation of an important image quality characteristic, such as brightness, for example, in order to determine the best point of view concerning this parameter. This approach could be extended to other parameters, depending on the characteristics of the image necessary for good detection. Also, this robot could be also used to achieve measurements on other crops, such as maize, wheat or sunflower, for various precision agriculture operations.

References

- Åstrand, Björn and Baerveldt, Albert-Jan. A mobile robot for mechanical weed control. Halmstad University, School of Information Science, Computer and Electrical Engineering (IDE), 2003. International Sugar Journal, ISSN 0020-8841, Vol. 105, no 1250, p. 89-95
- Barbedo J.G.A.. Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus, 2(1) :1, 2013.
- Bayle B., Fourquet J.Y., and Renaud M.. Manipulability of wheeled mobile manipulators : Application to motion generation. The International Journal of Robotics Research, 22(7-8) :565–581, 2003.
- Bock, C. H., Poole, G. H., Parker, P. E., and Gottwald, T. R. 2010. Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. Crit. Rev. Plant Sci. 29:59-107, USA.
- Craig J.J.. Introduction to robotics : mechanics and control. Pearson education international. Pearson, Prentice Hall, Upper Saddle River, NJ, 3. ed., international ed edition, 2005. OCLC : 249488662.
- Ding W., Li Y., Wang W., and Zou Y.. Vanishing point detection algorithm for urban road image based on the envelope of perpendicular and parallel lines. 34, 10. 2014.
- Gée Ch., Bossu J., Jones G., and Truchetet J.. Crop/weed discrimination in perspective agronomic images. Computers and Electronics in Agriculture, 60(1) :49–59, January 2008.
- Gustavo A. Pereyra-Irujo ^A, Emmanuel D. Gasco ^A, Laura S. Peirone ^A and Luis A. N. Aguirrezábal. a low-cost platform for phenotyping plant growth and water use. Functional Plant Biology 39(11) 905-913, 2012
- Henson J.M. and French R.C.. The Polymerase Chain Reaction and plant disease diagnosis. Papers in Plant Pathology, 31 :81–109, 1993.
- Hobbs H.A., Reddy D.V.R., Rajeshwari R., and Reddy A.S.. Use of Direct Antigen Coating and Protein A Coating ELISA Procedures for Detection of Three Peanuts Viruses. Plant Disease, 71 :747–749, 1987.
- Klose R., Penlington J., Ruckelshausen A.. Usability study of 3D Time-of-Flight cameras for automatic plant phenotyping. University of Applied Sciences Osnabrück/ Faculty of Engineering and Computer Science, Albrechtstr. 30 ; 49076 Osnabrück; Germany
- Kong H., Sarma S.E., and Tang F.. Generalizing Laplacian of Gaussian Filters for Vanishing-Point Detection. IEEE Transactions on Intelligent Transportation Systems, 14(1) :408–418, March 2013.
- Mahlein A.K., Steiner U., Hillnhütter C., Dehne H.W. and Oerke E.C.. Hyperspectral imaging for small-scale analysis of symptoms caused by different sugar beet diseases. Plant Methods 2012 8:3, Germany
- Montalvo M., G. Pajares, J. M. Guerrero, J. Romeo, M. Guijarro, A. Ribeiro, J. J.Ruz, and J. M. Cruz. Automatic detection of crop rows in maize fields with high weeds pressure. Expert Systems with Applications, 39(15) :11889–11897, November 2012.
- Paulus S., Behmann J., Mahlein A.K., Plumer L. and Kuhlmann H. Low-Cost 3D Systems: Suitable Tools for Plant Phenotyping. Institute of Geodesy and Geoinformation (IGG)—Geodesy, University of Bonn, Nussallee 17, Bonn 53115, 2014. Germany
- Rovira-Más F., Zhang Q., Reid J.F., and Will J.D.. Hough-transform-based vision algorithm for crop row detection of an automated agricultural vehicle. Proceedings of the Institution of Mechanical Engineers, Part D : Journal of Automobile Engineering, 219(8) :999–1010, August 2005.
- Sankaran S., Mishra A., Ehsani R., Davi C.. A review of advanced techniques for detecting plant diseases. Computers and Electronics in Agriculture 72 (2010) 1–13, USA
- Scharr H., Minervini M., French A.P., Klukas C., Kramer D.M., Liu X., Luengo I., Pape, G.J.M., Polder, D. Vukadinovic, X. Yin, and S. A. Tsafaris. Leaf segmentation in plant phenotyping : a collation study. *Machine Vision and Applications*, 27(4) :585–606, May 2016.
- Soetanto D., Lapierre L., and Pascoal A.. Adaptive, non-singular path-following control of dynamic wheeled robots. In Decision and Control, 2003. Proceedings. 42nd IEEE Conference on, volume 2, pages 1765–1770. IEEE, 2003.
- Spong M.W., Hutchinson S., and Vidyasagar M.. Robot dynamics and control. Wiley, New York, second edition edition, 2004.
- Subramanian R., Spalding E.P., Ferrier N.J. A high throughput robot system for machine vision based plant phenotype studies. 2012 at Springerlink.com.
- Yamamoto Y. and Yun X.. Coordinating Locomotion and Manipulation of a Mobile Manipulator. 1992.
- Yoshikawa T. Analysis and Control of Robot Manipulators with Redundancy. Robotics research : the first international symposium, pages 735–747, 1984.
- Zhang Y., Yan X., Chen D., Guo D., and Li W.. QP-based refined manipulability-maximizing scheme for coordinated motion planning and control of physically constrained wheeled mobile redundant manipulators. Nonlinear Dynamics, 85(1) :245–261, July 2016