2019-07-08

Soft manipulator robot for selective tomato harvesting

Mohamed, A

http://hdl.handle.net/10026.1/14873

10.3920/978-90-8686-888-9_99
Precision agriculture '19
Wageningen Academic Publishers

Soft Manipulator Robot for Selective Tomato Harvesting

A. Mohamed[1], J. Shaw-Sutton[1], B.M. Green[1], W. Andrews[1], E.J. Rolley-Parnell[1], Y. Zhou[2], P. Zhou[2], X. Mao[3], M.P. Fuller[4], M.F. Stoelen[1,5]
[1]University of Plymouth, School of Computing, Electronics and Mathematics, Drake Circus, PL4 8AA Plymouth, United Kingdom,
[2]Shanghai Jiaotong University (SJTU), School of Agriculture and Biology, Dongchuan Road 800, 200240 Shanghai, China, P.R.,
[3]Shanghai Sunqiao Modern Agricultural United Development Company, 185 Mianbei Road, The China (Shanghai) Pilot Free Trade Zone, 201210 Shanghai, China, P.R.,
[4]University of Plymouth, School of Biological and Marine Sciences, Drake Circus, PL4 8AA Plymouth, United Kingdom,
[5]Fieldwork Robotics Ltd, Drake Circus, PL4 8AA Plymouth, United Kingdom;
abdulla.mohammad@plymouth.ac.uk

Abstract

The harvesting of soft fruits and vegetables is a labour-intensive process, often representing more than 50% of the total costs for the producer. In this paper, a harvesting robot is proposed for tomato picking. The robotic solution is developed to address the needs of the tomato producers in the Shanghai region in China, one that faces population growth and therefore a higher demand on food supply. The robotic system presented here consists of a variable-stiffness manipulator arm, a soft robot gripper, and different types of sensors that are used to identify and locate in 3D and pick the tomatoes. The implemented variable compliance enables the robot manipulator to work in a semi-structured environment without damage to itself, the crop, or the surrounding. In this paper, the hardware and the software of the robot is described in detail. Early results from the first testing of a proof-of-concept on fresh tomatoes placed on artificial stems in Shanghai are presented, as well as picking UK tomato varieties in greenhouse conditions.

Keywords: Selective harvesting, soft robotics, tomatoes, variable-stiffness actuators.

Introduction

The increasing demand on farmers motivates research on agriculture robots for different applications such as seeding, weed control and harvesting. (Reddy et al., 2016). Many robots have been developed to work in harvesting for different fruits and vegetable. For example, Hemming et al. (2014) designed a robot for sweet-pepper, van Henten et al. (2002) proposed a robot for harvesting cucumbers and Leu et al. (2017) designed a robot for the harvesting of green asparagus.

Feng et al. (2015), proposed a robot for picking tomato within a greenhouse that uses an installed rail to travel between the tomato vines. A 4 degree-of-freedom (DOF) arm was used with a perception system that consisted of a CCD camera attached to the linear laser projector. The detection algorithm used to detect the tomato applied a threshold to HSI colour space. The same group (Feng et al., 2015) proposed a design for tomato grasping (Wang et al., 2016). A high success rate was reported (up to 83.9%), but experimental conditions and procedures were not detailed. Zhao et al. (2016), proposed another robot for tomato harvesting using dual-arms consisting of 3 degrees of freedom for each arm. Each arm had a different end-effector, one to hold the tomato using a pneumatic suction cup and the other equipped with a cutter to cut the stem of the tomato. A stereo vision system was integrated with the robot to locate the tomato positions. The robot proposed in Zhao et al. (2016) required a human worker to identify the ripe tomato.

Tomatoes are the world's largest vegetable category (Eurofresh, 2016), with a total production of around 130 Mt. China is among the 5 largest tomato producers. The project described in this paper is a collaboration between UK and China based research groups to design and develop a soft robot manipulator for tomato harvesting. The project aimed to explore a soft end-effector for gentle picking and separation of tomatoes without a cutting mechanism, and a variable-stiffness robot arm for operating in this complex horticultural environment. The proposed system was intended to have a fully autonomous detection, planning and picking loop, and used point clouds and a watershed algorithm for detection. The first proof-of-concept robot was tested briefly in greenhouse environments in both China and the UK, awaiting longer-term quantitative experiments.

Methods and Materials

Robot arm

The GummiArm is a robotic arm with seven DOFs inspired by the mechanisms of human and animal sensorimotor systems (Stoelen et al., 2016). The GummiArm can be considered soft robotics owing to the joint mechanisms that use agonist–antagonist actuators connected to the joints via flexible tendons. These actuators are able to control the stiffness of the joints during operation (Figure 1). Agonist-antagonist actuators can be described as a pair of linear actuators where the agonist actuator causes movement in a given direction, and the antagonist actuator opposes the torque induced by the agonist actuator to increase stiffness.

The GummiArm was originally developed at the University of Plymoth, UK, for research groups working on robots operating in complex and unpredictable environments. It is largely 3D printable to enable quick iterations on hardware, and the base version is available open source (GummiArmCE, 2018). It utilises Dynamixel (Robotis, Korea) digital servos. The environment during harvesting can be unpredictable, and detecting all hazards in the environment using sensors can be difficult (e.g. in most fruit plants, a thin string is used to support the plants). The GummiArm is therefore an interesting option to employ in this type of environment.

Gripper

The proposed gripper is mounted as an end-effector on the robot arm. It is a soft gripper with three fingers that deform to the shape of the object upon grasping. The body of the gripper is made of rigid Polylactic Acid (PLA) whilst the fingers are made from an elastic deformable polymer coated with high friction silicone. This decreases the likelihood of damage to the tomato. A Red, Green, Blue (RGB) camera integrated in the gripper is used for visual servoing and to provide data about a cluster of tomatoes. An Infra-Red (IR) sensor is used to measure the distance of the tomato to the gripper.

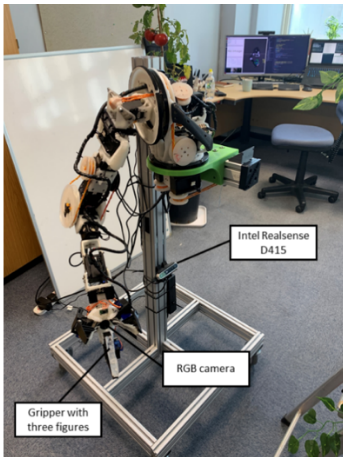

Figure 1: The robot arm, gripper, and sensors.

Camera systems

There are two cameras integrated with the robotic manipulator. The first sensor is a Realsense D415 (Intel, CA, USA) color/depth camera, see Figure *1*. This camera is used to detect and 3D locate the tomato in front of the robot. The second vision sensor is a USB camera integrated with the gripper (Figure *1*).

Software architecture

The software of the robot is based on Robotic Operation System (ROS) (Quigley et al., 2009). ROS is an open source system comprising a collection of libraries and software that are used to accelerate prototyping robots and share the experience between developers.

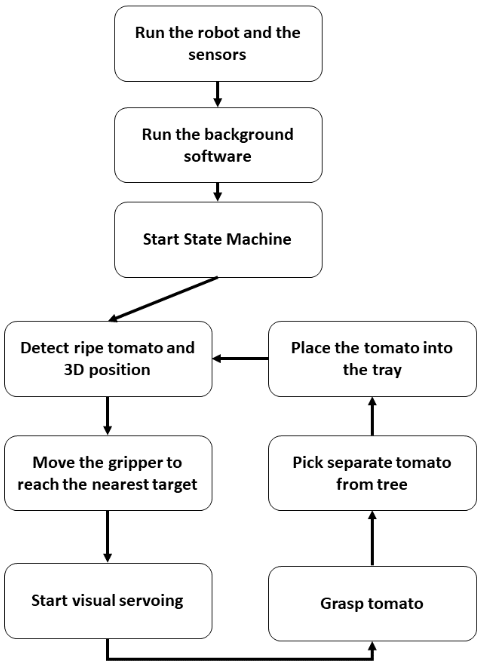

Figure 2: State machine of tomato harvesting

The state machine for the system was based on ROS and specifically tuned to tomato harvesting. In general, the state machine is a cycle of different processes as shown in Figure *2*. The cycle starts by (1) locating the 3D position of the fruit, (2) command the arm to move closer to the target, (3) a visual servoing process for precise positioning relative to target fruit, (4) close the gripper and pull the fruits to separate it from the plant, and (5) place the fruit in a tray. The following subsections describe each stage in detail.

Detection and 3D localisation of tomatoes

The first process in the state machine is the 3D detection of the tomato relative to the arm base. This process computes the position of the tomato using RGB image and depth data provided by Intel Realsense D415. Figure *3* shows the pipeline of the depth detection algorithm. The process starts by detecting the tomato in RBG image by applying a linear regression model to detect the tomato. The linear regression model applies to each pixel to compute the probability of said pixel corresponding to a tomato or not $P_{RGB} \epsilon (0,1)$.

$$P_{RGB} = X * w + B \quad (1)$$

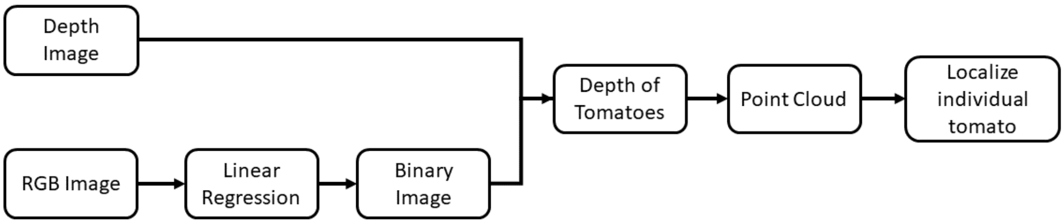

Figure 3: Detection and 3D localisation pipeline used.

The output of the linear regression process is a binary image used to mask the depth image using the bitwise process. The bitwise process is used to irelevant content from the depth image. The depth map is converted to point cloud format which is then used to compute the centroid of the detected tomato.

Visual servoing

The visual servoing is used in order to approach the tomato with greater precision than can be achieved from a more remote camera. The visual servoing node was designed to grip the tomatoes which are clustered so tightly that the 3D detection could not manage to detect the individual targets. The visual servoing uses the camera in the gripper where the process starts by detecting the tomatoes and then determines the tomato nearest to the centre of the image. The visual servoing detection algorithm is designed to identify each tomato separately using a watershed algorithm (Bleau and Leon, 2000). Figure *4* shows the input image from the gripper camera and the output image of the algorithm where the tomatoes detected are outlined. The output of the detection algorithm provides a 2D pixel co-ordinate (x, y), whereas the end effector manipulates in 3D, $P_e(X, Y, Z)$. An exponential function was used to compute the movement in the z axis of the image frame by computing the Euclidean distance (q) which is biased for greater movement with smaller distances.

$$z = \exp^{(q \times \lambda)} \times \beta \quad (2)$$

where β is the scaling constant which limits the range of the output to meet the image size and λ is the constant which describes the shape of the output.

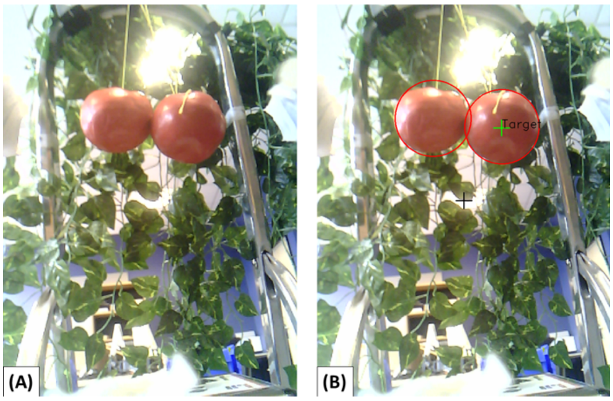

Figure 4: Visual servoing detection of individual tomato in the cluster. (A) camera image and (B) the output of the detection algorithm where the black cross is the centre of the image and the green cross indicates the target that is closest to the centre.

The output of the detection process is the difference between the position of the target and the centre of the camera image. A proportional controller is used to compute the error of the end effector position relative to the tomato position. This error added to the current position of the end-effector then feeds into the inverse kinematic model to compute the new joint angles that feed to the joint controller to move the arm to the new position. The K_p was selected based on trial and error.

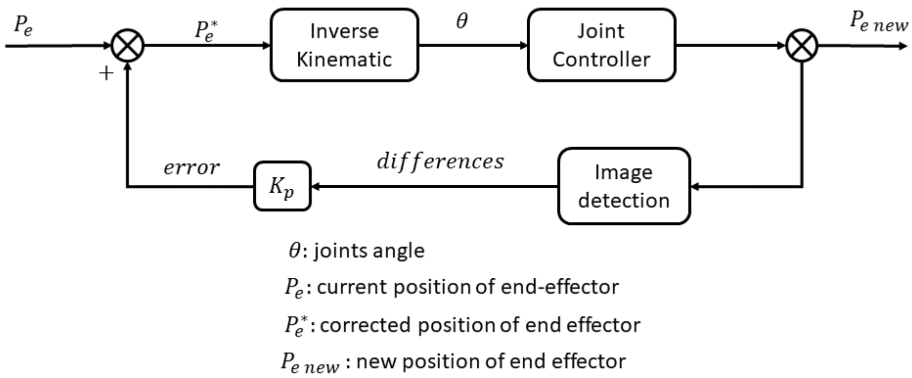

Figure 5: The visual servo controller used for the last part of the tomato-picking process.

Motion planning

As the robot manipulator is integrated with ROS the position of the end-effector is computed and controlled using the MoveIt! motion planning framework. MoveIt! provides an inverse kinematics planner and motion controller for the GummiArm by reading the Universal Robotic Description Format (URDF) file of the manipulator. The motion planning and control are used in different stages within the state machine, including positioning the end-effector in front of the detected tomato and placing the tomato in the tray after picking.

Experiment Setup

The system has been tested in greenhouses in the UK and China. Figure *6* shows the setup. The robot is placed in front of a tomato plant and initialised to pick the tomato with the shortest absolute distance to the robot base. This testing has been done to evaluate the robot performance in terms of picking success rate and the speed of picking by measuring the entire circle of the state machine. The time of each process in the state machine has been measured separately during the experiment in order to analyse the durations and identify any bottlenecks of the cycle. However, the first test in China has a more simplified setup due to the lack of ripe tomato plants at the time the test was performed (the setup was designed to simulate an authentic scenario).

Figure 6: Experiment setup (A) China, (B) UK, (C) Lab.

The principal target for the robotic system was the Chinese market, and the robot was therefore primarily designed for larger Chinese tomatoes (approx. 75 mm diameter). A range of UK varieties were also tested, and it was found that the solution can be adapted to regular UK varieties with small changes to the size of the gripper fingers. Further experimental work is needed to truly assess the quantitative performance and robustness of the system under commercial growing conditions, in terms of detection, maturity classification, and picking performance. This work is underway winter 2020 in Shanghai, China, with an improved version of the system.

Result and Discussion

The main advantage of using the robot in harvesting is accelerating the picking process and reduction of labour cost where the robot may work continuously. Therefore, the robot was tested and evaluated based on the speed of picking and the success rate of picking the tomatoes. Figure *7* shows the time of each step in the harvesting process starting with the 3D detection and ending with placing the tomato in to the tray. From Figure *7*, the timing leads to understanding bottlenecks in the state machine process which is currently in the visual servoing that take the longest time to finish. The main reason is the complexity of placing the gripper on the tomato in the best position. However, in the next iteration of the system, a depth camera will be integrated into the end effector in order to generate improved approach paths and more accurately position the gripper with regard to the target tomato.

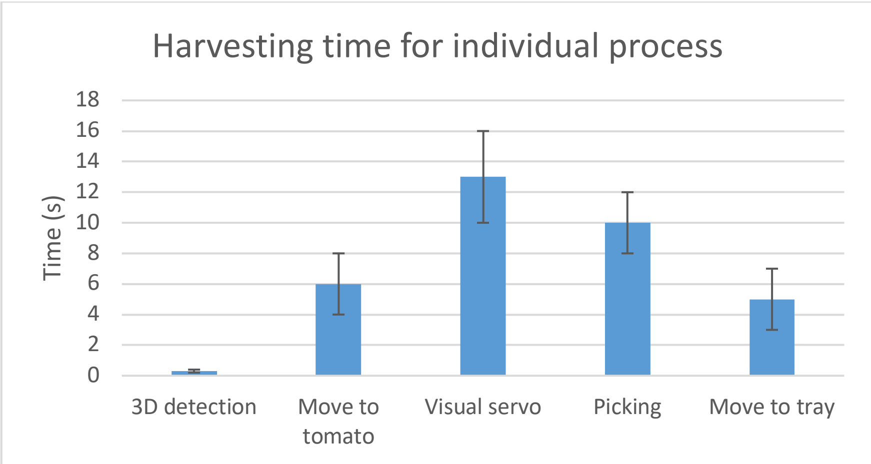

Figure 7: Time for each process in the state machine.

The complete picking process for picking one tomato was 30 ± 5 s. The 5 s margin error is due to the varying position of the tomato relative to the arm base. However, the time is comparable to the work of Feng et al. (2015), at 25 seconds. More work is needed to define benchmarking standards to make such comparisons more relevant.

In future work, the visual servoing process will integrate with a depth camera to improve both the speed and confidence of motion and determine the best pose of the gripper around the tomato. The state machine of the robot will be rewritten in order to improve the speed and the reliability of the picking process. More extensive benchmarking will also be performed on production crop.

Conclusion

This paper presents a soft manipulator robot for selective tomato harvesting, using human inspired motor mechanisms. Passive compliance was introduced in the picking process to help increase robustness to unforeseen impacts during autonomous operation. The robot integrates various types of sensor in order to detect, locate and pick ripe tomatoes. The software architecture was based on ROS, while using the MoveIt! framework for motion planning. A custom soft robot hand was designed to enable one-handed picking without a cutting mechanism. The robot has been through first tests in greenhouses in both China and the UK. The full cycle time for picking a tomato was 30 ± 5 s, but more extensive experiments are needed to assess performance and robustness on commercial crops.

Acknowledgement

The work presented here was funded by two grants from the Agri-Tech in China: Newton Network+ (ATCNN). The work also received support in-kind from Detao Shanghai Centre, Shanghai, China and Fieldwork Robotics Ltd, Plymouth, UK.

References

Bleau, A., Leon, L.J., 2000. Watershed-Based Segmentation and Region Merging. Comput. Vis. Image Underst. 77, 317–370. https://doi.org/https://doi.org/10.1006/cviu.1999.0822

Eurofresh, 2016. Around the World: Tomatoes. Accessed February 11th, 2019. https://www.eurofresh-distribution.com/news/around-world-tomatoes

Feng, Q., Wang, X., Wang, G., Li, Z., 2015. Design and test of tomatoes harvesting robot, in: IEEE International Conference on Information and Automation. pp. 949–952. https://doi.org/10.1109/ICInfA.2015.7279423

GummiArmCE, 2019. GummiArm Community Edition on GitHub. Accessed February 9th, 2019. https://github.com/GummiArmCE

Hemming, J., Bac, C.W., Tuijl, B., Barth, R., Bontsema, J., Pekkeriet, E., et al., 2014. A robot for harvesting sweet-pepper in greenhouses.

Leu, A., Razavi, M., Langstädtler, L., Ristić-Durrant, D., Raffel, H., Schenck, C., et al., 2017. Robotic Green Asparagus Selective Harvesting. IEEE/ASME Trans. Mechatronics 22, 2401–2410. https://doi.org/10.1109/TMECH.2017.2735861

Quigley, M., Gerkey, B., Conley, K., Faust, J., Foote, T., Leibs, J., et al., 2009. ROS: an open-source Robot Operating System, In: ICRA Workshop on Open Source Software.

Reddy, N.V., Vishnu, A. V, Reddy, V., Pranavadithya, S., Jagadesh Kumar, J., 2016. A critical review on agricultural robots. A Crit. Rev. Agric. Robot. Int. J. Mech. Eng. Technol. 7, 183–188.

Stoelen, M.F., Bonsignorio, F., Cangelosi, A., 2016. Co-exploring Actuator Antagonism and Bio-inspired Control in a Printable Robot Arm, In: Tuci, E., Giagkos, A., Wilson, M., Hallam, J. (Eds.), From Animals to Animats 14. Springer International Publishing, Cham, pp. 244–255.

van Henten, E.J., Hemming, J., van Tuijl, B.A.J., Kornet, J.G., Meuleman, J., Bontsema, J., et al., 2002. An Autonomous Robot for Harvesting Cucumbers in Greenhouses. Auton. Robots 13, 241–258. https://doi.org/10.1023/A:1020568125418

Wang, G., Yu, Y., Feng, Q., 2016. Design of End-effector for Tomato Robotic Harvesting. IFAC-PapersOnLine 49, 190–193. https://doi.org/10.1016/j.ifacol.2016.10.035

Zhao, Y., Gong, L., Liu, C., Huang, Y., 2016. Dual-arm Robot Design and Testing for Harvesting Tomato in Greenhouse. IFAC-PapersOnLine 49, 161–165. https://doi.org/10.1016/j.ifacol.2016.10.030