Development of an Experimental Strawberry Harvesting Robotic System

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Abstract: This paper presents the development of an integrated strawberry harvesting robotic system tested in lab conditions in order to contribute to the automation of strawberry harvesting. The developed system consists of three main subsystems; the vision system, the manipulator and the gripper. The procedure for the strawberry identification and localization based on vision is presented in detail. The performance of the robotic system is assessed by the results of experiments that take place in the lab and they are related to the recognition of occluded strawberries, the check of the strawberries for possible bruises after the grasping and the accuracy of detection of the strawberries' location. The results show that the developed vision algorithm recognizes correctly every single strawberry and has high accuracy in recognizing occluded strawberries in which the largest part of each of them is visible. A small localization error results in a correct grasp and cut without causing damage to the fruit.

1 INTRODUCTION

The agriculture sector is changing due to the use of new technologies such as automation, providing significant benefits to the farmers. This paper deals with the automation in the harvest of strawberries, one of the most popular and profitable berries. The strawberry farmers around the world face serious problems of labor shortage, due to the tedious working conditions and the general social and financial conditions. Today, the growth of strawberries in table-top cultivation (see figure 1) is very common, something that facilitates the robotic harvesting process as the berries are more approachable and they differentiate from the leaves. In this way, harvesting robots offer quality, higher productivity, as they can operate during the whole day, and more profits to the producers without having to modify the layout and the size of their cultivation.

The actions that take place in harvesting is the detection, the approach, the grasp and the placement of the strawberry in a little box. In order to automate this procedure, these actions must be accomplished by a robotic system, which should contain at least a computer vision system for the detection localization of the mature fruit, a manipulator for the movement of the gripper towards the grasping of the fruit.

A suitable robot vision system must include methods for the recognition and the localization of the strawberry. The recognition of the strawberry is used for the quality control of the fruit such as the check of the maturity, the existence of diseases and damages in the fruit. These methods that were implemented for other fruits can also be used for the strawberry case with some modifications. The mature fruits are usually recognized by using color based methods (Slaughter and Harrell, 1987), by measuring a fraction of the mature region of the strawberry over the immature region (Hayashi et al., 2009) and (Feng et al., 2008). The recognition of disease existence is very useful as the defective strawberry must be separated by the healthy ones and it is implemented by an image segmentation method (Narendra and Hareesha, 2010).

The exact detection of strawberries' place is the most challenging point in the automated harvesting as the strawberries can be occluded from other strawberries, leaves and other objects. There have been de-

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Figure 1: Strawberries in table-top cultivation.

veloped methods to solve this problem with various success rates. (Stajnko et al., 2004) used a thermal camera (LWIR) in combination with an image segmentation method in order to analyze the apple crops by taking advantage of the difference in infrared radiation between the fruit and the leaves. The success rate of this method was increased, if the pictures were taken in the evening, when there is a high difference in temperature between the apples and the environment. (Yang et al., 2007) proposed a 3D stereo vision system and color based image segmentation to distinguish effectively the tomato clusters, but they did not achieve the separation of each tomato from their cluster as the tomatoes had the same depth. (Nguyen et al., 2014) made use of the redness of each pixel in the colorful image of the RGB-D camera in order to distinguish the apple from its background, implemented the RANSAC algorithm, and obtained the location of the center of each detected apple by using an iterative estimation method to the partially visible target object data.

Object classification methods were used on top of the image segmentation to face the occlusions. These methods create a model for the object to be detected, using image training samples in different variations. The Viola-Jones algorithm (Viola and Jones, 2001) is very efficient in real time object detection as its cascade structure makes the classifier extremely rapid. (Puttemans et al., 2016) applied a semi-supervised fruit detector for strawberries and apples by using these object classification techniques. The detection accuracy was improved in comparison to the previous methods, but only for the fruits that were used as training samples and there is the problem of the precise characterization of a sample as positive or negative. (Li et al., 2018) use a deep learning method in order to recognize elevated mature strawberries. A neural network was trained in order to recognize overlapping and occluded strawberries. This achieves very high accuracy in the detection and the low average recognition time makes it suitable for real-time machine picking, but the deep network training requires a lot of iterations for a high rate of accuracy and capturing and processing a huge amount of learning samples of strawberries images. The cutting points on the peduncles of double overlapping grape clusters are detected in (Luo et al., 2018). The edges of the clusters are extracted and the contour intersection points of the two overlapping grape clusters are calculated based on a geometric model, but there is the limitation of non detection more than two overlapping grape clusters.

In previous works, various types of grippers have been developed in order to assure a sufficient grasp of the strawberry without causing damage to this. A common type of gripper consists of a scissor which cuts and holds the strawberry by his peduncle in order to avoid possible damage of the fruit. In addition, (Hayashi et al., 2009) used a suction device which holds the fruit before its separation from the peduncle if the localization error is small. (Hemming et al., 2014) developed a gripper whose fingers adapt to the fruit. It also contained a cut mechanism of the fruit. These types of grippers have some drawbacks, as the use of scissors lets a piece of the stem on the strawberry which is undesirable and the suction device may cause serious damage to the fruit. (Dimeas et al., 2015) designed and constructed a system which grasps and cuts the strawberry in the way that a laborer would do. The localization of strawberry with respect to the fingers is achieved using haptic sensor and a fuzzy control system controls the force to be applied to the strawberry for correct hold. The separation of fruit from the peduncle is done by rotating the grasped strawberry by 45°.

In this paper, a robotic system for strawberry harvesting is presented with emphasis to the vision recognition and localization of the crop. The vision system is based on a modified approach presented in (Luo et al., 2018) and adapted to strawberries. The Kinect V2 sensor is used and the integration of the system is made in ROS. The methods for the object detection, image segmentation based on the color model, the feature detection and the object classification are presented. The system is tested for occluded crops and for various features, such as, position accuracy, success of removal and crop damage in a single crop.

The remaining of the paper is organised as following: In the next section the proposed method is presented briefly. The analysis of the integrated system with emphasis to the vision methods and the experimental results are presented in sections 3 and 4 respectively. Finally concluded remarks are closing this paper.

2 THE PROPOSED APPROACH

The structure of the system is illustrated in Figure 2. The sensor Kinect V2 for Windows depicts the robot vision system, the robotic manipulator represent the strawberry approach system and the gripper is the grasping system. These subsystems are connected to a PC where runs the software that is developed for the purpose of this work.

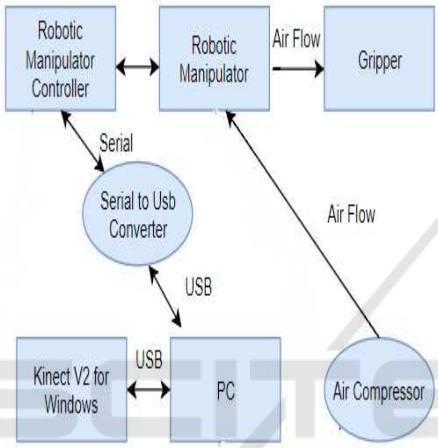

Figure 2: Hardware structure of the developed robotic system.

As it is mentioned in the introduction, the main points for object detection are the image segmentation based on a color model, the feature detection and the object classification. Since the strawberry has the uniform red color and spores on its surface, the accuracy of a feature detection method is too low. Taking into account these limitations and the demand for a huge number of samples in order to create a reliable model in the object classification technique, an image segmentation method based on a color model is applied. In this direction, a suitable color model is used, between the various available models, that represents in an obvious way the color of the strawberries. After image pre-processing, a threshold, that distinguishes the pixels of the strawberries than the pixels of the background, is selected. Furthermore, an algorithm is developed based on the geometry of the strawberries' clusters in order to separate the strawberries that belong to the same cluster.

After the successful recognition of the strawberry and the computation of its center of mass, the distance of the detected strawberry from the robot end-effector is estimated. For this estimation, a depth sensor or the capture of images from two different points can be used. The depth sensors' performance is quite influenced by the lighting conditions which have significant variations in the outdoor environment. Moreover, these sensors have a remarkable error in depth estimation as the distance of the object from the camera increases. The second method requires the existence of two cameras or one moving camera. In the case of strawberries, it is difficult to implement this technique as they have a lot of same features on their surface so it is tough to find the position of a certain point in both images. As the experiments are done in lab conditions, where the lighting conditions are steady and controllable and the strawberries can be in a distance where the depth sensor's error is low, the sensor Kinect for Windows v2 is used, mounted on a fixed base, to estimate the strawberries' position in 3D space. For the development of the computer vision algorithms, the OpenCV library is used.

In a previous paper (Dimeas et al., 2013), the movement of the labourers' arm was studies and the design of the gripper's movement was based on this. The robotic manipulator for the experiment is the MITSUBISHI RV-A4 which has 6 DoF. In order to grasp the strawberry, an open source three- fingered design of a robot gripper is adapted, manufactured using a 3D printer and mounted on the manipulator's arm.

In terms of the software of the system, Robot Operating System (ROS) framework in a Linux operating system and C++ as the programming language are used.

3 VISUAL IDENTIFICATION AND LOCALISATION OF THE STRAWBERRY

The main sensor for the visual identification and localisation of the strawberry is the Kinect which has a monochrome CMOS sensor capable to observe the infrared light. It is placed at an offset relative to the IR emitter, and the difference between the observed and the emitted IR dot positions is used to calculate the depth at each pixel of the RGB camera. The 'libfreenect2' open source driver for the Kinect for Windows v2 device is used (Xiang et al., 2016). The iai_kinect2 is used which includes tools and libraries for the ROS interface of this sensor (Wiedemeyer, 2015). The implementation of the visual identification and localisation of the strawberry is based on the OpenCV software library.

The following algorithm for the robot vision system is developed:

- The vision sensor is initialized and a color image and a depth image are obtained by using a camera grabber software package that is developed in the ROS framework.
- The RG image (see Figure 3) is obtained using the following formula:

$$I_{rg} = \begin{cases} I_r - I_g, & \text{if } I_r \geq I_g \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

  where $I_r, I_g \in 0, \ldots, 255$ are the intensity of the pixels at the red and the green channel respectively. These two channels are chosen as the mature strawberry is red and the leaves are green.
- In order to select an optimal threshold, the RG image is segmented using the OTSU method (Otsu, 1979) and a binary image is derived. Morphological transformations such as dilation and erosion are used in a suitable sequence in order to fill holes in the identified areas and to reduce the noise in the binary image. In figure 5.a and figure 5.b the binary image after the segmentation and after the morphological transformations are shown, respectively.

Figure 3: Result of applying the RG formula in an image. (a) Original Image (b) Image after RG formula.

- The contours of the clusters of strawberries are determined using the findContours function of OpenCV (Bradski, 2000) which implements a border following algorithm (Suzuki et al., 1985).
- For the j-th cluster, where $j \in 1, \ldots, nc$ and nc is the number of the clusters in the image, the far-left and the far-right points in the x-direction are determined and connected with a line. The positive directions x and y and the beginning of the coordinate frame are illustrated at the right image of the figure 5. The space of the binary image D_{bin} is defined as

$$D_{bin} = \{(x,y) \in R^2 : x \in (0,w), y \in (0,h), I_{bin}(x,y) = 0 \text{ or } 255)\} \quad (2)$$

where w and h are the width and the height of the image respectively and $I_{bin}(x,y)$ is the intensity of the binary image at the pixel (x,y).

Therefore, for each cluster the far-left point (x_l, y_l) and the far-right point (x_r, y_r) are:

$$(x_l, y_l) \in \{(x,y) \in D_{bin} : x_l = \min x \ \ \forall x \in cluster\, j\}$$
$$(x_r, y_r) \in \{(x,y) \in D_{bin} : x_r = \max x \ \ \forall x \in cluster\, j\} \quad (3)$$

Then the diagonal line of each cluster is found in order to classify the points of the contour of each cluster in upper and down points and the equation of this line is the following:

$$(-y) = \frac{(-y_r) - (-y_l)}{x_r - x_l}(x - x_r) + (-y_r) \quad (4)$$

- For each cluster, the points of their contours are separated in upper and down points by comparing their coordinates with the line designed in the previous step. So a point (x_u, y_u) belongs to the upper part of the cluster, which is symbolized as the set UC_j, if the following inequality holds.

$$(-y_u) > \frac{(-y_r) - (-y_l)}{x_r - x_l}(x_u - x_r) + (-y_r) \quad (5)$$

  Otherwise it belongs to the down part of the cluster, which is the set DC_j.
- The k local upper points, which are candidate regions of the contours of the two images of the two strawberries which intersect, (x_{tukj}, y_{tukj}) of each cluster j are found by comparing the y value of each point $\in UC_j$ with the corresponding y values of its neighbor points, in the x-direction neighborhood, and are defined as breaking points (x_{bukj}, y_{bukj}). In case that there are many breaking points in a narrow area in the x-direction due to the non uniformity of the found contour, then the breaking point is considered to be the median point between them as there is no possibility of a large distance between these points because of the geometry of strawberries' shape at the breaking points. In a cluster j, if there are i breaking points, it means that there are $i+1$ strawberries in this cluster.
- The corresponding lower breaking point of each upper breaking point is the point of DC_j that has the minimum Euclidean distance from the upper breaking point i.e.

$$(x_{bdij}, y_{bdij}) = \{(x,y) \in DC_j : mindist((x,y),(x_{buij}, y_{buij}))\} \quad (6)$$

  Then the corresponding upper and lower breaking points are connected with a line and after we find the contours of each cluster of strawberries by using the findContours function of OpenCV (Bradski, 2000). The previous steps are illustrated in the figure 4.

- The new contours are considered as strawberries if their area satisfies a constraint that is defined by taking into account the geometry of strawberries' shape. The strawberries are considered to be conical, but since the image is two-dimensional the formulas for the area of a triangle are used.
- The center of each contour that corresponds to a strawberry is determined by using the 1^{st} and 2^{nd} order moments, $(x_c, y_c) = (\frac{M_{10}}{M_{00}}, \frac{M_{01}}{M_{00}})$.
- The orientation of strawberry is computed by using Principal Component Analysis (PCA) (Bradski, 2000). The angle of the eigenvector with the largest eigenvalue corresponds to the main (larger in length) axis and provides the orientation of the strawberry in the image plane.
- The point cloud that is created is stored in the memory like a one-dimensional matrix. The value of the matrix at the index that corresponds to the center (x_c, y_c) of the strawberry shows the depth of the strawberry i.e the distance of the strawberry with respect to the camera frame.

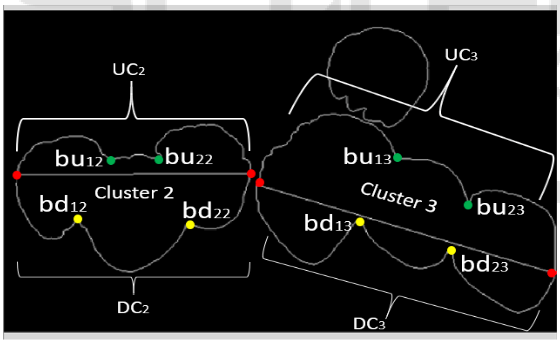

Figure 4: Explanation of the geometric model. The red dots show the far-left and far-right points, the green dots show the breaking points of the upper part and the yellow points show the down part of each of the clusters 2 and 3. Also, the diagonal line of the equation (4) for each of the clusters 2 and 3 is presented.

4 ROBOTIC MANIPULATOR AND GRIPPER

As the strawberries are detected and their locations in 3D space are determined, then the robotic manipulator moves the gripper to the position of the strawberries with an orientation defined according to the strawberry orientation. The robotic manipulator has

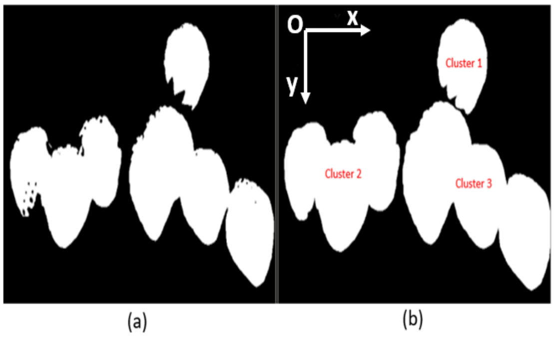

Figure 5: (a) Segmenting the RG image (b) Morphological transformations in the binary image.

6 DoF, the maximum load that it can hold is 3kg so it bears the weight of the mounted gripper and its workspace is sufficient in order to approach the strawberries. The manipulator's controller receives the extracted coordinates of a strawberry and its orientation and uses them as a reference signal for the movement of the gripper towards grasping the specified strawberry.

A gripper is designed and 3D printed (Figure 6). The drafts of the main part of the gripper are open source (Bieber, 2016). The fingers of the gripper adapt to the strawberry since they are quite flexible. The outside part of the finger is more compact than the inside part in order to present a resistance to the cut of the fruit and also the gap between the three fingers is such that the fruit does not slip after grasping The components of the gripper are made by using a 3D printer. The gripper is actuated pneumatically by a simple open-loop ON-OFF control logic.

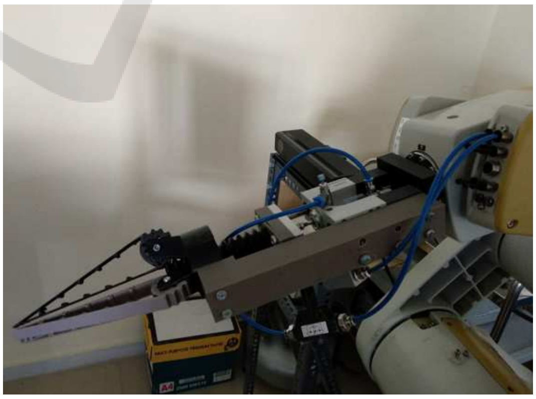

Figure 6: Gripper of the robotic system.

5 EXPERIMENTAL ROBOTIC SYSTEM

The software for the experimental system is implemented in the Linux operating system and in particular the 16.04 version of Xubuntu using ROS. Apart from the developed software packages, some available ROS packages are used e.g the actionlib package. The use of the actionlib package in our system is shown in figure 7.

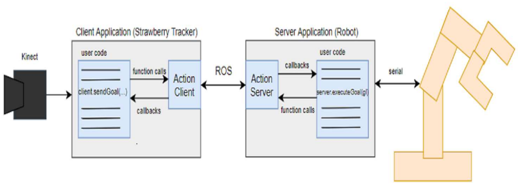

Figure 7: Overview of ROS client-server interaction in the robotic system.

The graph of the operation of ROS in shown in figure 8. In this work, the main developed ROS package is the StrawberryHarvester. The ros nodes that are included in the StrawberryHarvester package are shown inside the ellipsoids that are the camera_bridge, which is responsible for the beginning of the kinect sensor's operation, the definition of the topics for the camera info, the color image and the depth image, and the definition of camera parameters such as the image resolution. Then the node strawberry_tracker subscribes to the topics /camera/image_color_rect, /camera/image_depth_rect and /camera_info in order to obtain the color and depth images and create the point cloud which publishes to the topic /camera/points afterward. Also, the nodes strawberry_tracker and the robot communicate through the action move_robot.

The functional diagram of the strawberry harvesting robotic system is shown in the Figure 9. When the strawberries are located and their positions with respect to the sensor's coordinate frame are computed, then these positions are transformed with respect to the coordinate frame of the robot, so that they are sent to the robotic manipulator's controller.

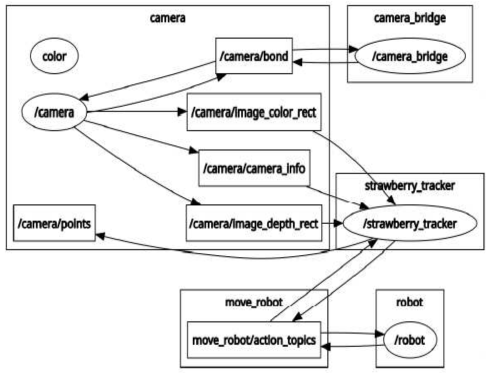

Figure 8: ROS operation graph.

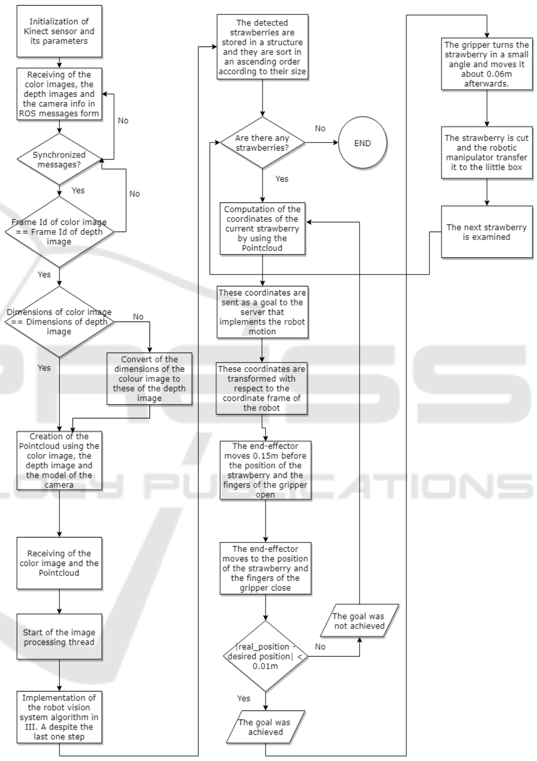

Figure 9: Flowchart of function of the robotic system.

6 EXPERIMENTAL RESULTS

Two types of experiments were carried out in order to evaluate the developed system: (a) Recognition of separate and occluded mature strawberries. (b) Evaluation of the harvesting process for single strawberries.

The developed algorithm for recognition of strawberries has a great success rate. In the case of the single strawberries, the success rate is 100 % as in a number of 30 images it recognized correctly all the strawberries. In the case of the occlusion, the algorithm distinguishes the strawberries only if their largest part is visible, i.e. the 60% of their area is not occluded by other object or if the gap between the upper points of the fruits is not large enough to consider a breaking point as it is illustrated in Figure 10 in which the first from the left strawberry in the right cluster is not separated from the adjacent strawberry that is located in front of it. This is due to the fact that the edge in the upper contour of these two strawberries does not show a dip.

The recognition and the detection of a strawberry

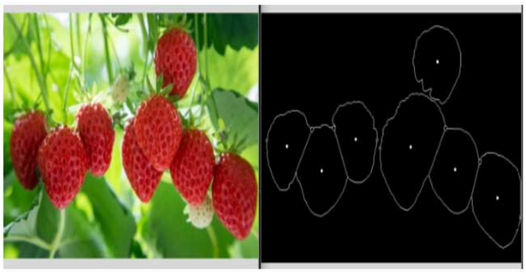

Figure 10: (a) Occluded strawberries (b) Result of applying the vision algorithm in occluded strawberries.

during the experiment is represented in figure 11. The harvesting experiment was set up by hanging fresh strawberries with their peduncles on a metal structure and putting some green cloth in order to simulate the leaves and the immature strawberries. The calibration of the sensor took place several times before the experiment until achieving a good result in the 1^{st} experiment. Finally, the developed strawberry harvesting robotic system is evaluated by repeating the harvesting process a lot of times, in which the strawberries are located in different positions around the field of view of the camera and by checking the correctness of the recognition, the accuracy of the localization, the way of gripping the strawberry, the correctness of the crop removal from the peduncle and the existence of damages in the strawberry after the harvest. The results are listed in Table 1.

Figure 11: Recognition and detection of a strawberry during experiment.

According to Table 1, the mean error along the X,Y,Z directions of the robot base coordinate frame is 0.45cm, 0.335cm and 0.11cm respectively. Therefore, the mean error is inside the acceptable limits which are 1cm in each direction. Also, it is shown that the accuraccy of recognition and localization is 90% i.e. 18 out of the 20 cases. In the 4^{th} experiment the error is high which is due to the visual field and the distortion lens of the sensor and to the accuracy of the calibration. In this case, the strawberry was placed far from the center of the image where generally the lens distortion is larger. In the 8^{th} experiment, the error along the x direction is high as the strawberry was far from the robot base and out of its workspace. In the 18^{th} experiment, the gripper goes a bit righter than the position of the strawberry so it does not remove it correctly after.

To sum up, the experimental results show that the robotic system identifies occluded strawberries and localize the mature separate strawberries with great accuracy (90%) and large correct harvesting rate (85%). The recognition and localization accuracy is a bit larger than the 87% true positive rate in sweet-peppers detection of (Hemming et al., 2014), the 88% recognition accuracy in overlapping grape clusters (Luo et al., 2018) and the 85% rate of correct detection in occluded apples (Nguyen et al., 2014). But, it is smaller than the 95% average recognition rate by using a deep learning method in recognizing strawberries. As regards, the success rate in harvesting, our system shows a little bigger correct harvesting rate of 85% in relation to the 80% of (Hayashi et al., 2009).

With reference to the situation of the strawberry after the harvest, the results showed that the gripper grasped and cut the strawberry without causing damage to its outer surface and deteriorating the quality of the fruit. In a sample of 20 strawberries, only one had some bruises which is justified by the fact that some strawberries remained long time detached from the plant. The images in figure 12 depict the situation of a strawberry at both sides before and after the harvest. A video of the recorded harvesting process is available at this link (Klaoudatos et al.,).

7 CONCLUSIONS

In this paper, a robotic system for strawberry harvesting is developed and tested in laboratory conditions. A new method for the recognition and localisation of occluded mature strawberries is developed. A flexible gripper is built for grasping the strawberry and it is tested with good success in grasping and removing the strawberries without damaging them. The laboratory experimental results show that the developed system is able to recognize occluded crops and localize the mature separate strawberries with high accuracy and large successful harvesting rate. Future work will be focused on using larger sample of strawberries, as now the experiments with 20 samples of strawberries are initial experiments, and on achieving higher rate of recognition of quite occluded strawberries using machine learning algorithms and the incorporation of an autonomous mobile robot in order to harvest the strawberries in real conditions.

Table 1: Results of the experiment.

No	Position error in cm	Correct Grasp	Correct Cut	Damage
1	(0,0,0)	yes	yes	no
2	(0,0.3,0)	yes	yes	no
3	(0,0.3,0)	yes	yes	no
4	(0.4,1.3,0.8)	wrong position	no grasp	no grasp
5	(1,1,0)	yes	yes	no
6	(1,1,0)	at the edge of fingers	yes	no
7	(0.5,0,0.3)	yes	yes	no
8	(2,0,0.3)	out of workspace	no grasp	no grasp
9	(0,0.3,0)	yes	yes	no
10	(1,0.3,0)	at the edge of fingers	yes	no
11	(0.5,0,0)	yes	yes	no
12	(1,0.8,0.4)	a bit sideways	yes	no
13	(1,0,0)	yes	yes	no
14	(0,0,0)	yes	yes	no
15	(0,0.2,0.3)	yes	yes	no
16	(0.3,0.1,0.1)	yes	yes	no
17	(0.3,0,0)	yes	yes	no
18	(0.1,1,0)	sideways	no grasp	no grasp
19	(0.4,0.1,0)	yes	yes	yes
20	(0,0,0)	yes	yes	no

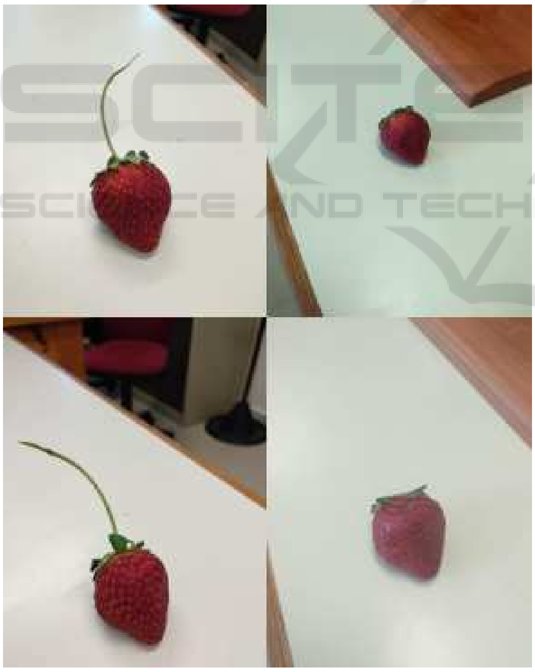

Figure 12: At the left column is the strawberry before the harvest in both sides and at the right the respective after the harvest.

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