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Towards automated strawberry harvesting: Identifying the picking point

Zhuoling Huang[1], Sam Wane[2], and Simon Parsons[1]

[1] Dept of Informatics, King's College London, UK
{zhuoling.huang,simon.parsons}@kcl.ac.uk
[2] Harper Adams University, UK
swane@harper-adams.ac.uk

Abstract. With the decline of rural populations across the globe, much hope is vested in the use of robots in agriculture as a means to sustain food production. This is particularly relevant for high-value crops, such as strawberries, where harvesting is currently very labour-intensive. As part of a larger project to build a robot that is capable of harvesting strawberries, we have studied the identification of the picking point of strawberries — the point that a robot hand should grasp the strawberry — from images of strawberries. We present a novel approach to identify the picking point and evaluate this approach.

Keywords: Agricultural automation, harvesting, computer vision

1 Introduction

Strawberries are an important cash crop, and are grown all over the world. China, which is the largest producer and exporter of strawberries [3] produced 33.13 million tonnes of strawberries in 2014 [9]. However, strawberry production is quite labour intensive. According to research from Japan [2], the labour cost of harvesting strawberries alone can reach 900 hours per hectare, and this is only about 45% of the whole labour cost. This high labour cost makes the idea of using robots in strawberry production, and in particular strawberry harvesting, an attractive option. This is not a new idea, and the first patent concerning a strawberry harvesting robot was published in 1996 [1]. In recent years, more and more research has been done in this area. According to the data provided by the State Intellectual Property Office of China in November 2016 [14], Japan has the largest number of patents concerning strawberry harvesting robots, while in the past three years China has seen the largest increase in the number of such patents, followed by the US.

This increase in the number of patents for strawberry harvesting robots reflects the growing interest in using robots in agriculture. This in itself is part of a wider, and longer standing, trend towards greater automation in agriculture, and planting and harvesting of crops at a larger scale. This trend is increasingly driven by the fertility decline and consequent aging population in many developed countries, which is projected to lead to labour shortages in agriculture. (Indeed, in many developed countries, including the UK, agriculture already relies heavily on migrant labour for harvesting.) Agricultural robots are seen by many as a necessary solution to all these problems. As a result, many kinds of robot have been invented to harvest vegetables and fruits, such as apples, oranges, and so on [5], making it possible to automate the harvest of many high-value fruit and vegetables[3]. However, berries, including strawberries and other soft fruit are much harder to harvest using robots. This is for several reasons. First, many berries are not spherical, making them harder to identify than fruit like apples and oranges. Second, the berries need to be harvested ripe, when they are soft, and this means that they need careful manipulation — squeezing them can cause them to become rotten quickly. This not only ruins individual berries, but, because the rot spreads, can cause widespread damage to a crop. As a result, strawberries and other soft fruit present challenges that mean that existing methods for fruit harvesting will not work.

As part of ongoing work towards the development of a strawberry harvesting robot, we are currently working on image processing to detect ripe strawberries. Detecting strawberries to pick, of course, is a necessary precursor to actually picking them. In this paper we describe a method for detecting ripe strawberries, and a new approach to identifying the *picking point*, the place on the stem of the strawberry where a harvester should aim to detach the strawberry from its parent plant. Compared with previous approaches, we dealt with images that included more "noise" in the background in the form of unripe strawberries, stems, and leaves. Our method uses the OHTA colour space to detect a target strawberry, and then calculates the slope of the stem of this strawberry based on the lowest point of the fruit and the centroid of the fruit. Then a candidate picking point is selected by finding a strawberry stem that has this slope.

The rest of this paper is structured as follows. Section 2 describes related work on image processing to detect fruit. Section 3 then describes our approach. Section 4 describes experiments that we carried out to test our method, and Section 5 gives the results of those experiments. Section 6 then concludes.

2 Related Work

According to the literature, the process of harvesting can be divided into three steps: mature fruit detection, fruit position location and fruit picking. We describe the most relevant work on these steps.

For fruit picking, there are three main methods to achieve the goal. One method is to separate the fruit and the branch by dragging the fruit or bending the branch by holding the fruit. For example [15] describes harvesting pineapples in this way. However doing this may easily damage strawberries, since the fruit is generally softer than pineapple. Another method for picking fruit is for

[3] Of course, the harvesting of crops such as grain has been heavily automated for a long time.

a robot hand, or a special cup, to hold the fruit, as described in [18]. In [18] a stationary robotic strawberry harvester was introduced, with the aim of dealing with strawberry plants which grow on a table-top or a shelf. In this work, a camera detected the maturity of the fruit from the side of the bench, while another camera located the position of strawberry from below. Viewing the strawberry from below is advantageous since from below the shape of strawberry is circular and so the fruit could be detected more easily than from the side. Nozzles, both horizontal and vertical, were used to blow adjoining strawberries away from the target strawberry. The harvesting success rate for this method was 67.1%. The final method for picking is to detect a suitable picking point for the fruit, a point that is typically on the stem that joins the fruit to the plant — the *peduncle* rather than on the fruit itself. This point can then be grabbed with a manipulator without damaging the fruit. This is the preferred method of harvesting many soft fruits as well as some other crops such as peppers [12].

[11] introduced the basic idea for detecting the picking point when harvesting tea shoots. [17] described a way to identify the picking point of oranges. When the orange reaches its lowest position during the pendulum movement, the picking point should be right above it. Thus, combined with the Circular Hough Transform (for detecting the orange itself), the picking point can be detected. [8] talked about finding the picking point of grapes. Grapes and branches were distinguished by colour difference, and then the Hough Transform was applied to the images of branches to find straight lines. The distance from the barycentre of the fruit to each straight line was calculated, and among them the midpoint of the line with minimal distance would be regarded as the picking point of the bunch of grapes. The accuracy of this method was shown to be higher than 85% when detection was performed during the day time. [16] introduced the design of a litchi picking manipulator, which included consideration of detecting the picking point. The litchi peduncle and the fruit were detected by colour, then the point in the image of the peduncle with maximal distance from the fruit cluster's centroid could be regard as the picking point. The accuracy of detecting the suitable picking point reached 94.2%. [7] introduced a method to find the picking point of tomato clusters. The minimal enclosing rectangle of a tomato cluster's boundary and the centroid were used to find the picking point, which was defined as the intersection point of a vertical line crossing the centroid and the upper edge of the rectangle.

Despite all this research, and the economic importance of strawberries, there has, as yet, been little work on detecting the picking point of strawberries. For strawberries, the picking point is on the stem, a centimetre or two above the calyx, so detecting the stem of the strawberry is important. T. Zhang [20] studied finding the picking point of a strawberry 2005, and, to our knowledge, and this is the first publication studying strawberry stem detection. According to [20], the picking point should be in on the projection a line between the peak of the strawberry and the centre of gravity of the strawberry. Since the strawberry is roughly conical, the peak of the fruit could be defined as the furthest point from the centre of mass. We found that this method worked best when the strawberry was of uniform density. No results on the performance of the method were reported in [20].

A few years later, Guo [4] used the principal axis of inertia of the strawberry to describe the position and the posture of the strawberry stem in order to detect the picking point. [4] reports a success rate for stem detection of 93% when working on images of strawberries with a pure colour background in a laboratory environment. This represents a relatively simple environment in which to perform stem detection, and later work by [6], who used a combination of images taken in the field, and images of strawberries taken from a Google image search, found the approach to be less effective— [6] reports a 26.9% success rate. More recently, [19] introduced a strawberry picking robot which uses the centroid of the strawberry and the axis of symmetry through the centroid to detect the picking point. This paper does not determine the accuracy of selecting the picking point, but does report that experiments gave an accuracy rate of 88% for picking mature strawberries, suggesting that the rate of selecting the picking point is no less than 88%. [19] used a somewhat more realistic environment than [4] for testing While [4] used strawberry branches cut from the plant, and placed on a pure colour background, [19] used strawberry plants in the green house, but hid extra strawberries and stems, covering the shelves used to grow the strawberries with a plastic film[4]. Note that the main difference between [4] and [19] is the move from laboratory to greenhouse and the use of a picking robot in the latter paper — the vision problem in both cases is very similar, with the task being simplified so that the images are easy to segment and the stem is easy to locate. In addition, both [4] and [19] used *Akihime* strawberries for their experiments. Akihime is a variety of strawberry which produces particularly long heart-shaped strawberries with low rate of producing ill-shaped fruit.

The latest work on this topic is [6], already mentioned above in the context of their critique of [4]. [6] investigates a method which is based on the Blum medial skeleton of the strawberry boundary. From the skeleton, three extreme points can be detected as key medial points to generate a triangle. The triangle is then used to describe the shape of the strawberry, and the stem can be identified from elements that are perpendicular to the base of the triangle. This method has a reported accuracy rate of 71%, which is much higher than the method using the principal axis of inertia (26.9%) on the images tested in [6]. However, this method only pointed out the possible area of stem selection — it outputs a bounding box around what is identified as the stem — and it does not identify the specific stem that was attached to the target strawberry from the others that may be in the background.

3 Method

Our method can be divided into three parts: image preprocessing, strawberry detection and picking point detection. The whole method is shown in Figure 1.

[4] This setup can be seen in the images in [19].

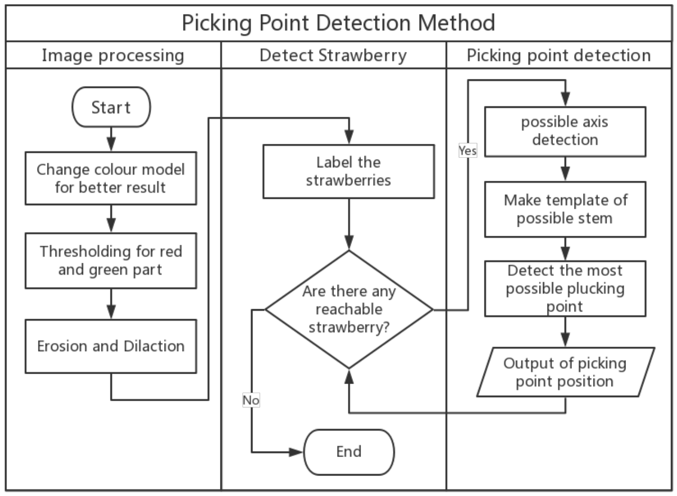


Fig. 1. The method we used for picking point detection.

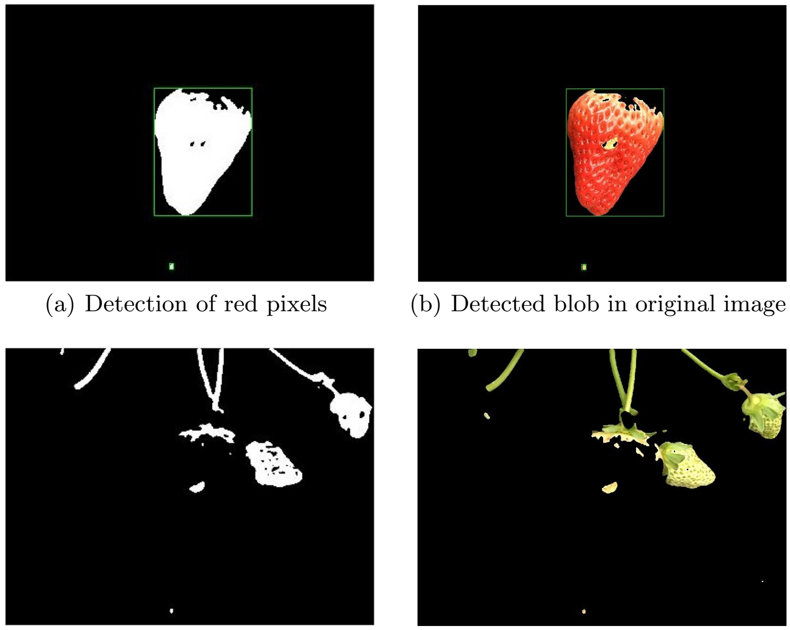
3.1 Image preprocessing

We start with standard RGB images, but quickly found that it is hard to detect strawberries and stems directly using the RGB colour model. As a result, we adopted the OHTA colour model, proposed by Ohta et al. [10]. This is a linear transform of the RGB colour model:

$$I_1 = \frac{R+G+B}{3}$$
$$I_2 = R - B$$
$$I_3 = \frac{2G-R-B}{2}$$

where R, G and B refer to the usual red, green and blue colour values respectively, in the range of $[0, 255]$.

Having applied this transform, we followed [13] in using a colour histogram to help identify suitable thresholds to segment strawberries and stems from images. We then used these thresholds to carry out a simple colour segmentation of ripe strawberries and stems. Sample results of this segmentation can be seen in Figure 2. (The original image is shown in Figure 5(d).) Figure 2(a) shows the result of the segmentation of an image containing a ripe strawberry, where pixels that have passed the threshold for a ripe strawberry are shown in white. Figure 2(b) gives some context to the previous image by showing these pixels as they appear in the original image. Figure 2(c) shows the same image, but after segmentation using the colour threshold for the strawberry stem, again with all the pixels that have passed the threshold shown in white, and Figure 2(d) shows



(a) Detection of red pixels (b) Detected blob in original image

(c) Detection of green pixels (d) Detected blob in original image

Fig. 2. Examples of colour segmentation of red (ripe strawberry) and green (stem and unripe strawberry) areas of an image. The original image is Figure 5(d)

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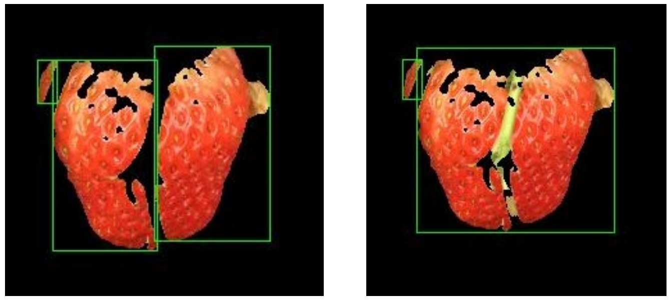
the same, but replacing the white pixels with the corresponding pixels from the original image. Looking at these four images together shows that while colour segmentation does a good job of identifying ripe strawberries, detecting stems (and hence the picking point) is more complex. There are multiple stems in the image, so deciding which one corresponds to the ripe strawberry is non-trivial, and the image also contains green, unripe, strawberries, which can segment with the stems.

Now, Figure 2 also shows us that although the thresholds have been chosen carefully, there are still some small pieces of background that have been segmented with the ripe strawberry and the stems, while some parts of those objects have not been detected. To refine the results of the segmentation, we therefore apply both erosion and dilation to mitigate these problems. Erosion deletes small segmented areas that are not connected with other segmented regions, and dilation helps to fill in small gaps in segmented regions.

A further issue, and one that is still apparent after applying erosion and dilation, arises when a ripe strawberry in the original image is behind a stem. In such a case, the segmented ripe strawberry appears cut into a number of smaller pieces. To fix this, the gaps between pieces caused by stems should be filled. To ensure that we do not "complete" spurious gaps, we first test that the



(a) (b)

Fig. 3. Merging pieces of the same strawberry. (a) shows a ripe strawberry, that is crossed by a stem, after segmentation. (b) shows the same strawberry after the segmented image is "filled in" by the stem.

width of the gaps are within the range of the width of stems that we find in the image, and we also check that any pixels which are resegmented as a result have been segmented as stems. The result of this process can be seen in Figure 3. Figure 3(a) shows a large ripe strawberry that has been bisected by a stem. Figure 3(b) shows the pixels that are resegmented to complete the strawberry. In the completed image, the stem pixels are shown in their original green. The process we follow is presented as a flowchart in Figure 4

3.2 Strawberry detection

Following the pre-processing stage, the image has been segmented into regions that correspond to ripe strawberries ("red" regions) and regions that correspond to stems or unripe strawberries ("green" regions). Here we briefly describe how the red regions are processed to identify ripe strawberries. There are two issues. First, we have to ensure that regions that were segmented separately but represent a single strawberry whose image is crossed by a stem (as above) are handled as a combined region. Second, we have to ensure that we distinguish between strawberries that are near enough to pick, from those that are further away. This latter problem is particularly acute because in many commercial settings, such as that pictured in [19], strawberries are grown in raised beds so that the strawberries hang down for easy picking. These beds are often raised on pillars, and that means that an image can contain ripe strawberries from both the near side of the bed, strawberries that are accessible, and ripe strawberries from the far side of the bed, strawberries that are not accessible.

The first of these issues is a simple matter of book-keeping. After the initial segmentation, separate red segments are labelled uniquely. When we detect that two segments, as in Figure 3(a), are part of the same strawberry (as described above), we have to relabel them as belonging to the same segment. The second issue is also easily handled. We assume that the size of ripe strawberries will be similar, and the images of the smallest strawberry will be no smaller than λ

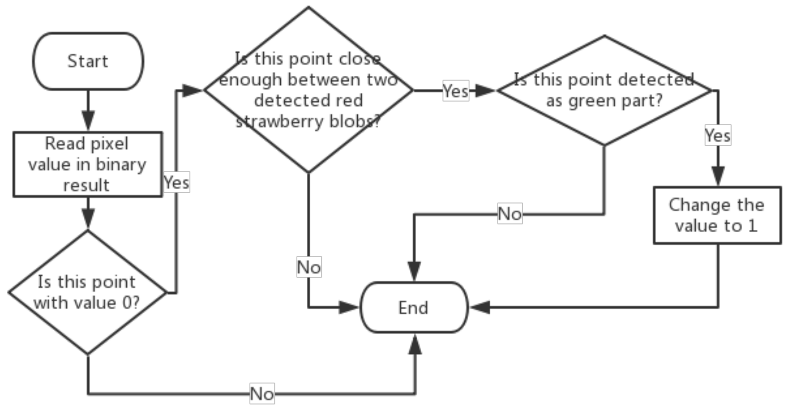


Fig. 4. The re-segmentation process for ripe strawberries.

percent of size of the largest one. where size is determined by the count of pixels in the red segment. Then red segments smaller than this size will be regarded as strawberries on the other side of the bed and therefore unreachable. In our experiments, λ was set to 50%.

3.3 Picking point detection

As a strawberry stem is a herbaceous stem, and thus uses turgor pressure to hold the fruit, it is not strong enough to support a strawberry fruit from the bottom. Instead, strawberries are usually pendulous, with the stems bending downward. Hence, when harvesting strawberry, the picking point — the point at which to hold the fruit and sever the stem — is on the stem a centimetre or so above the calyx. A natural way to model the position of the stem as an oblique line — if we can identify this line, then it is easy to position the picking point on it. To identify the line, we first need to identify two fixed points on that line.

We use the lowest point in the fruit and the centroid of the fruit as the two fixed points which define the gradient of the line. From the segmented image, both the lowest point and the centroid are easy to find. The centroid can be found from:

$$\overline{x} = \frac{\sum\sum x \cdot f\left(x,y\right)}{\sum\sum f\left(x,y\right)}$$
$$\overline{y} = \frac{\sum\sum y \cdot f\left(x,y\right)}{\sum\sum f\left(x,y\right)}$$

where $f(x, y)$ returns 1 if the pixel at (x, y) is in the red segment and 0 if it is not. Once we have the gradient, we use template matching to find the picking

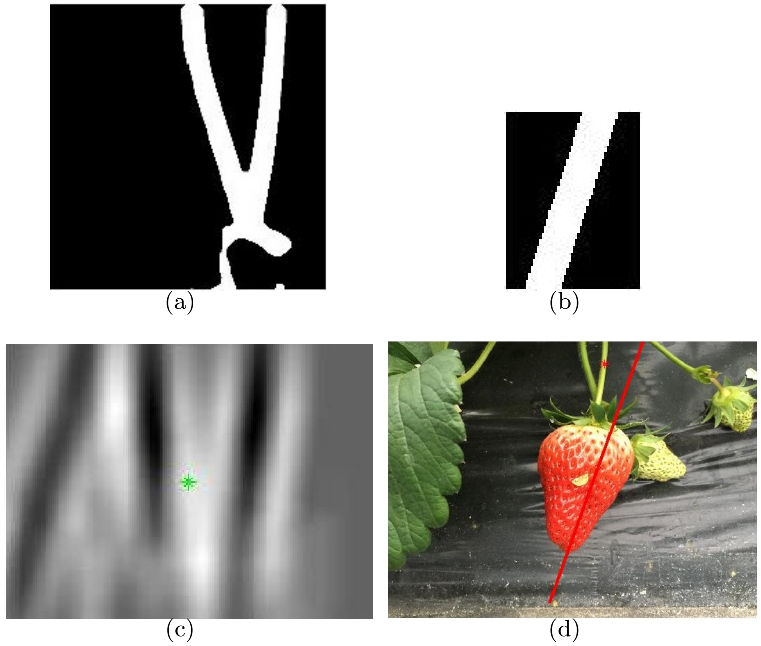


Fig. 5. Picking point detection: (a) shows the search area above the strawberry; (b) shows a stem template oriented as the line from lowest point to centroid; (c) shows the likelihood of points to be selected as the picking point, plus, in green, the most likely point; and (d) shows the original image with the selected picking point in red, and the line from the lowest point through the centroid is also drawn in red.

point, searching the part of the green segment just above the highest point of the strawberry. We look for elements of the image that match the template, a small segment of line with the width of a typical strawberry stem and the same gradient as the line from the lowest point to the centroid.

The template matching part of our method is illustrated in Figure 5. The initial image is shown in Figure 5(d). (This is the same image was we saw being segmented in Figure 2.) After segmenting the image (as in Figure 2) and identifying the strawberry, the area in which we search for the picking point is shown (somewhat magnified) in Figure 5(a). This area is chosen to limit the picking point to be within a suitable distance of the calyx. The stem template for this image is shown in Figure 5(b). This has been rotated to match the gradient of the line between centroid and the lowest point of the fruit. The result of template matching is shown in Figure 5(c). This takes into account both the degree of matching with the template, and the distance of a given point from the calyx. Brighter areas are areas which, as a combination of degree of matching and proximity to the calyx, are more likely to be a good picking point. Figure 5(c) shows the most likely picking point as a green dot, and this is shown as a red dot in the original image in Figure 5(d). The dot is on the stem above the ripe strawberry.

The reason for combining template matching and gradient is to enable our method to pick the most likely stem from a number of stems in an image. It is this aspect that makes our approach quite different from Zhang's [20] and Guo's [4] work. In both these papers, the authors only used images of single strawberries placed in front of a pure colour background, so only one possible stem ever appeared in the images, and hence there could be no confusion over which stem was connected to the target strawberry.

4 Experiments

In order to test how this method works, we took 185 pictures of Benihoppe strawberries in a commercial growing field in Jinhua, China. All of these pictures included at least one ripe strawberry that could be detected, and 7 images included two strawberries. Thus, overall we tested on 192 strawberries. Since there is no existing effective method for separating overlapping ripe strawberries, no such images were included. However, images with ill-shaped strawberries and ripe strawberries slightly covered by other unripe ones or leaves were included. We consider that 15 strawberries out of the total of 192 are ill-shaped[5], and 45 of the strawberries are partially obscured by leaves or unripe strawberries. The colour segmentation that we described above clearly identified every strawberry, so our results for picking point selection were obtained on all 192 strawberries.

As mentioned previously, both [4] and [20] used oblique lines to detect possible position of the strawberry picking point, and they are thus similar to the part of our method which detects the possible slope of the strawberry stem. We therefore also tested these two methods. As a result, for each image in our test set, we used three methods for identifying the gradient of the stem:

1. The gradient of a line crossing the lowest point of the strawberry blob and its centroid. This is the approach we developed. We call it the *nadir-centroid* (NC) method, because it uses the lowest point (nadir) of the fruit and the centroid to detect the stem.
2. The gradient of a line crossing the peak of the strawberry and the centroid of the blob. This is the method suggested by [20]. We call it the *peak-centroid* (PC) method because it uses the peak of the strawberry and the centroid.
3. The principle axis of inertia of the strawberry. This is the method suggested by [4]. We call it the *principle axis* of inertia (PA) method.

Each of these gradients was then used, as described above, with template matching to detect the most likely picking point. The three methods are illustrated in Figure 6. For each method, a dotted line and a star is placed on the image. The line is line that the method uses to set the gradient of the stem that it is searching for, and the star is the picking point that the method selects. The line and star for the NC method is shown in yellow, those for the PC method are in blue, and those for the PA method are in red.

[5] This is a subjective estimate since the concept of "ill-shaped" is itself ill-defined.

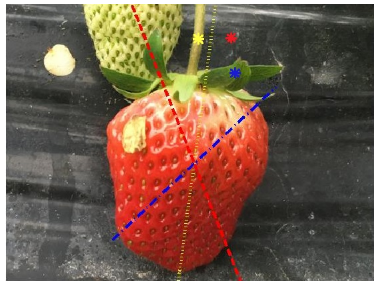


Fig. 6. The output of the three different methods on a sample image. NC is in yellow, PC is in blue, and PA is in red.

Note that the PC and PA methods are not exactly the methods suggested by [20] and [4]. Neither of those approaches used the template matching approach to locate the picking point. Rather both used simpler methods — in [20] an absolute offset from the calyx and in [4] the intersection of the axis of inertia and a line through the centres of mass of the green segments — that did not work in the more complex environment that we were using. As a result, we are comparing the ability of the methods to suggest a stem angle and thus to select a template.

5 Results

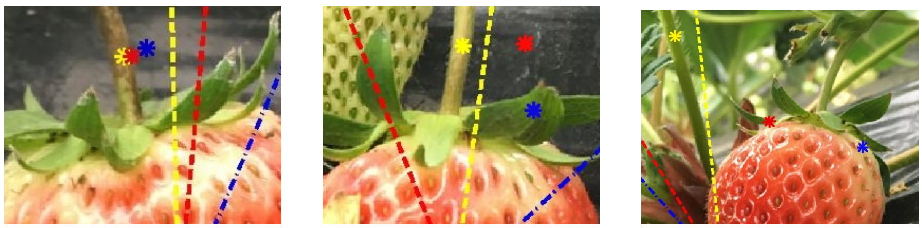
For each image, we predicted the position of the picking point using the methods described above. We then projected the point back onto the original image (just as in Figure 5(d)). As shown in Figure 7, the different methods give rather different results on some images. In Figure 7, just as in Figure 6, the picking point selected by NC is shown by a yellow star, the picking point selected by PC is shown by a blue star, and the picking point selected by PA is shown by a red star. When the star appears exactly on the stem of target strawberry, we consider that the picking point has been successfully selected. When the star appears on another stem, on the background or anywhere on the strawberry itself, including the calyx, we consider that the picking point has not been successfully selected. For example, in Figure 7(a), the red and yellow stars are on the target stem and so are counted as successful selections, while the blue star on the mulching film will not be regarded as a successful selection[6]. Similarly, in Figure 7(b), only the yellow star represents a successful picking point selection, while in 7(c), none of the methods have detected a suitable picking point since none of the stars fall on the stem of the ripe strawberry.

The accuracy of the three methods on our 192 strawberries is shown in Table 1. These results suggest that the NC method, which uses the lowest point of

[6] Though arguably it is close enough that a robot hand grabbing at this point might well connect with the stem.

Points used to compute gradient	Accuracy
Lowest point and centroid (NC)	84.38%
Strawberry peak and centroid (PC) [20]	60.42%
Principle axis of inertia (PA) [4]	53.65%

Table 1. Accuracy of detecting picking point



(a) (b) (c)

Fig. 7. Three examples of the three methods. In each picture the yellow star is the picking point selected by the NC method, the blue star shows the picking point selected by the PC method, and the red star shows the picking point detected by the PA method. In (a), PA and NC correctly detect the picking point, and PC does not; in (b) only NC correctly selects the picking point; in (c) none of the methods correctly selects the right picking point.

the strawberry and the centroid is the most accurate method of the three for selecting the picking point. Of course, in our experiments, the NC approach does not match the accuracies reported in [4] and implied in [19][7]. We believe that this is because, unlike the images used for testing by [4] and [19], our test images were taken in the field in its natural state. As a result, the background in our images is more complex, including mulch film, soil, dropped petals, leaves and other strawberries and stems. In addition, the strawberries in our images include many more ill-shaped strawberries — ones that diverge from the classical heart shape — making it harder to describe their shape and to identify both strawberry and picking point. This hypothesis is supported by the fact that when we used he NC method on images of strawberries which, like those in [4], were placed on a pure colour background, we obtained an accuracy of over 98%.

We believe that the extra complexity of the environment also accounts for the fact that the accuracy we obtained for the PA method is not as high as that reported in [4], where it was introduced (though we do obtain much better results for our version of the PA approach than [6] did) Tests on images of strawberries against a pure colour background, where we obtained 92% accuracy for PA, support this hypothesis. Since [20] did not report results, we cannot compare our results for the PC approach to previous results.

[7] Recall that [19] did not report accuracy of picking point, but a harvesting rate of 88% implies that picking point selection was at least 88% accurate.

(a) (b)

Fig. 8. Strawberries that are hard to detect. (a) is a typical ill-shaped strawberry; (b) is a ripe strawberry that is obscured by unripe strawberries.

A more complex background is one reason for the poor performance of PA and PC. Other factors that we believe contribute are as follows. As shown in Figure 6 the deviation of the strawberry from the classic shape means that the method [20] used to find the peak of the strawberry (defined as the furthest point from the centroid of the strawberry blob) is not that effective for ill-shaped strawberries. For similar reasons, the principle axis of inertia also lost its power to find the possible slope of stem in such cases. However so long as the strawberries are suspended and so are subject to gravity, the lowest point of the strawberry can still be used to find the probable slope of the target stem with reasonable precision, and this explains why the NC method performs with higher accuracy than the other two. The NC approach also outperforms the reported accuracy of [6], which also used more realistic images of strawberries than previous work, though we did not replicate their approach to determining the position of the stem so have no direct comparison on our image set.

Finally, we should discuss the cases in which the NC approach did not successfully select the picking point. There are three main reasons for the NC method to fail on our test images. First, the shape of the ripe strawberry is sometimes too strange even to use the lowest point to predict the slope of the stem. Such a case is shown in Figure 8(a). Secondly, some strawberries and stems are too obscured, by mud or by other parts of the strawberry plant, to get an accurate estimate of the lowest point or of the centroid. Such a case is an shown in Figure 8(b). Thirdly, a stem in the background might be sufficiently similar in angle to the target one that the NC approach has no way of knowing which stem is the right one. In such a case the approach can easily pick the wrong stem.

The number of each kind of failure is shown in Table 2. This shows that the main reason for failure is that either the stem or part of the strawberry fruit is obscured, and dealing with this issue is an area of ongoing work. (It is an area where we think machine learning could help.) However, note that the method does not fail on every ill-shaped or partially obscured strawberry — there were 15 ill-shaped strawberries and 45 strawberries were partially obscured — and so is already somewhat robust.

Reasons for failure	Number of instances
Ill-shaped strawberry	4
Too much of the strawberry is obscured	14
Similar stem detected	2

Table 2. Reasons for failure when detecting picking point

6 Conclusions

We have introduced a novel approach to detecting the picking point of strawberries and evaluated its effectiveness on a large number of images taken in the field. Our approach was found to be accurate, correctly identifying the picking point of strawberries 84% of the time, despite the complexity of the images, which exceeded that of methods introduced in two landmark papers on strawberry stem detection [4, 20] when these were tested on our image set. Indeed, using the core stem identification methods of [4, 20], augmented with some new elements to deal with the more complex images, on our set of images, produced much lower accuracies than reported in papers such as [19, 20], and much lower accuracies than were achieved with our method.

There are several areas in which our approach can be improved. For now, our approach, like all existing approaches that we know of, cannot handle cases in which two ripe strawberries overlap. These are seen as a single strawberry, and any calculation of picking point is hopelessly inaccurate. Similarly, if there are many stems in the image that are close to the stem of the target strawberry, our approach can get fooled into detecting the wrong stem. These are cases where our method sees too much strawberry or too much stem. Another situation in which our approach does not perform well is where strawberries are heavily obscured, by other pieces of plant, or by mud. In such cases, our approach does not see enough strawberry to correctly locate the lowest point and/or the centroid. Similarly, detection of the stem is sensitive to the stem being obscured by mud or other material that is not the right colour. All of these problems are examples of common problems for techniques, like ours, that rely on simple colour segmentation. While colour is a good guide, in some situations we will need more. Our current thought is that supervised machine learning, along the lines described in [12], is one way to try and improve our approach.

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References

1. Arima, S., Kondo, N.: Japan Patent No. JP3493801B2. Japan Patent Office, Tokyo (1996)

2. Chen, L.: Study on Picking System for Strawberry Harvesting Robot. Ph.D. thesis, China Agricuitural University (2005)
3. Food and Agriculture Organization Corporate Statistical Database. Food and Agricultural Organization of the United Nations Statistics Division (November 2016), http://www.fao.org/faostat/en/#data/QC
4. Guo, F., Cao, Q., Masateru, N.: Fruit detachment and classification method for strawberry harvesting robot. International Journal of Advanced Robotic Systems 5, 41–48 (2008)
5. Jimenez, A.R., Ceres, R., Pons, J.: A survey of computer vision methods for locating fruit on trees. Transactions of the ASAE 43, 1911–1920 (2000)
6. Leonard, K., Strawbridge, R., Lindsay, D., Barata, R., Dawson, M., Averion, L.: Minimal geometric representation and strawberry stem detection. 13th International Conference on Computational Science and Its Applications (2013)
7. Liang, X., Zhang, Y.: Recognition method of picking point for tomato cluster. Journal of Chinese Agricultural Mechanization 37, 131–134, 149 (2016)
8. Luo, L., Zou, X., Xiong, J., Zhang, Y., Peng, H., Lin, G.: Automatic positioning for picking point of grape picking robot in natural environment. Trans. Chinese Society of Agricultural Engineering 31, 14–21 (2014)
9. National Bureau of Statistics of China Statistical Database. National Bureau of Statistics of China (November 2016), http://data.stats.gov.cn/easyquery.htm?cn=C01&zb=A0D0L&sj=2014
10. Ohta, Y.I., Kanade, T., Sakai, T.: Color information for region segmentation. Computer graphics and image processing 13, 222–241 (1980)
11. Pei, W., Wang, X.: The two-dimension coordinates extraction of tea shoots picking based on image information. Acta Agriculturae Zhejiangensis 28, 522–527 (2016)
12. Sa, I., C, Lehnert, English, A., McCool, C., Dayoub, F., Upcroft, B., Perez, T.: Peduncle detection of sweet pepper for autonomous crop harvesting: Combined colour and 3D information. Report 1701.08608, arXic (2017)
13. Sezgin, M., Sankur, B.: Survey over image thresholding techniques and quantitative performance evaluation. Journal of Electronic Imaging 13, 146–165 (2004)
14. Patent search and analysis. State Intellectual Property Office of the PRC (November 2016), http://www.pss-system.gov.cn/sipopublicsearch/patentsearch/searchHomeIndex-searchHomeIndex.shtml
15. Wu, P., Hua, J.: The practical design of pineapple-picking robots. Journal of Lanzhou Institute of Technology 23, 58–61 (2016)
16. Xiong, J., Zou, X., Peng, H.: Design of visual position system for litchi picking manipulator. Trans. Chinese Society of Agricultural Engineering 43, 250–255 (2012)
17. Xiong, J., Zou, X., Peng, H.: Real-time identification and picking point localization of disturbance citrus picking. Trans. Chinese Society of Agricultural Engineering 45, 38–43 (2014)
18. Yamamoto, S., Hayashi, S., Yoshida, H., Kobayashi, K.: Development of a stationary robotic strawberry harvester with a picking mechanism that approaches the target fruit from below. Japan Agricultural Research Quarterly 48, 261–269 (2014)
19. Zhang, K., Yang, L., Wang, L., Zhang, T.: Design and experiment of elevated substrate culture strawberry picking robot. Trans. Chinese Society of Agricultural Engineering 43, 156–172 (2012)
20. Zhang, T., Chen, L., Song, J.: Study on strawberry harvesting robot: II. images based identifications of strawberry barycenter and plucking position. Journal of China Agricultural University 10, 48–51 (2005)