Strawberry ripeness calibrated 2D colour lookup table for field-deployable computer vision

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Abstract. Efficient strawberry harvesting using semi-autonomous robotic pickers requires a method for fast, automatic discrimination between ripe and unripe berries. In this paper we present a strawberry ripeness algorithm that has been developed and tested on images obtained with commercial cameras, recorded under daylight illumination on an outdoor strawberry farm. The method uses a 2D lookup table seeded such that regions for ripe strawberry, unripe strawberry and strawberry calyx exist in distinct locations in the table. Measurements show the ratio of ripe to unripe area provides a good estimator of ripeness and that the approach was practical for further extension to real-time use.

1. Introduction
In recent years the post-harvest processing of fruit has become a highly automated process reliant on technology rather than manual labour. The use of cameras and machine vision has improved the speed and efficiency with which processes such as grading and sorting are carried out [1-3], reducing costs to the producer and consumer. Fruit harvesting on the other hand remains a largely manual process, but progress is being made on automation for a variety of fruits [4].

Strawberries, with a high value and high labour costs are particularly attractive for semi- and fully-automated harvesting solutions, particularly as in the UK, labour shortages are becoming increasingly more challenging [5].

Once picked, strawberries cease ripening [6] and have short shelf lives, so it is important to pick them at the right time to maximise acceptance by the consumer. Therefore, fast and accurate computer vision algorithms are required to quantify strawberry ripeness for a pick decision. Unripe strawberries are green-white in colour, due to the presence of chlorophyll in their skin. As ripening progresses, patches of red, caused by anthocyanin, emerge and increase in surface area [6]. Therefore, an obvious way to define a strawberry’s ripeness from a computer vision perspective is to ratio the amounts of ripe and unripe surface area to produce a ripeness factor.

Determining which areas are ripe and unripe requires colorimetry [7], quantification of spectral reflectance across the visible spectrum. A spectrometer could be used to measure the reflectance spectrum, from which an accurate determination of colour can be calculated [8]. However, due to the measurements being taken with a fibre optic device, acting effectively as a single pixel, only a limited area can be inspected at a time. Scaling this up to provide multiple readings from each strawberry would slow down a harvester. Hyperspectral cameras, on the other hand, would allow images to be captured much like conventional cameras, but also take spectral readings for every pixel in the image with a resulting significantly higher cost than a conventional camera. Spectrometers and hyperspectral cameras
could provide the necessary spectral measurements, but as a harvesting robot will already deploy single or multiple conventional cameras for berry location, a method to utilise these same cameras is preferential. Conventional cameras are much lower cost than spectrometers and hyperspectral cameras, but spectral information is not directly provided.

In this paper we present a strawberry ripeness estimation method that uses a lookup table to segment the ripe and unripe areas from an RGB camera image and is suitable for deployable computer vision systems. It was designed as part of the AUTOPIC project to develop a prototype autonomous robotic strawberry picker. As part of the robot’s modular functionality, the ripeness estimation module was designed and ran separately from the strawberry detection module. The ripeness estimation module was also required to allow manual setting and intervention of the range of acceptable ripenesses that the robot picked. The paper presents an overview of the approach, lookup table structure and utilisation on test images obtained at an outdoor, commercial strawberry farm. Unlike other strawberry ripeness evaluation methods [9-12] our tests are undertaken in an outdoor environment rather than laboratory or on enclosed conveyer belts conditions.

2. Lookup table method

2.1. Chromaticity coordinates

Commercial colour cameras provide three component values at each pixel forming the image: red, green and blue \((R, G, B)\). The colour seen by an observer depends primarily on the relative values of these components, and to a much smaller extent on their absolute values, whose sum relates to the overall intensity at the image point. It is difficult to achieve a good accuracy in correcting the observed intensity for prevailing lighting conditions [8]. It is therefore convenient to normalise the three values by dividing by their sum, giving \(R/(R+G+B)\) etc., which eliminates the overall intensity and yields three “chromaticity coordinates” \((r, g, b)\) whose total is unity for the red, green and blue component values. The colour can then be defined by just two of the three numbers. Given the red and green coordinates, blue is implicit as the difference from unity.

2.2. 2D colour lookup table

To segment an image of a strawberry into different regions based on colour, one may define an acceptable range of values of each chromaticity coordinate for every defined region requiring segmentation. These ranges are then applied to every pixel in the input image to check whether it meets the requirements for any of the segmented regions. An alternative approach to this is to use a colour lookup table. This is an arrangement of all possible combinations of colours reproducible using the chromaticity coordinates assigned to the table’s dimensions.

Using the red and green chromaticity coordinates, \(r\) and \(g\), a basic two-dimensional table with \(n \times n\) elements can have dimensions \(K\) and \(L\) defined as \(K = nr\) and \(L = ng\) respectively. For this work a value of \(n = 255\) was chosen due to standard commercial cameras producing 24-bit colour images with each colour having integer values between 0 and 255. When appropriate \(K\) and \(L\) are rounded to the nearest integer values. The resulting table, illustrated in figure 1, has the colours distributed in a triangular region covering only half of the table’s available elements, since \(K + L\) has a maximum value of \(n\). As a coordinate \((K, L)\) may be obtained by more than one combination of \(R, G\) and \(B\), corresponding to differences in intensity, Figure 1 shows the colours with \(R, G\) and \(B\) scaled so that their values are as large as possible.
2.3. Modified lookup table

It would be more acceptable to an operator to make use of the full table by removing the blank region. Pictorially this can be done by stretching the yellow midpoint of the triangle’s green-red edge into the lookup table’s vacant corner, as in figure 2. The resulting arrangement of colours is like that of the Natural Colour System [13], in which a fourth basic colour, yellow, is introduced to the standard red, green and blue.

The procedure adopted for modifying the coordinates is illustrated in figure 3. A typical location P with coordinates \((r, g)\) is moved along the diagonal line \(P_R P_Y\) to a position \(P_1\) with coordinates \((k, l)\). With \(P_R P_Y\) at 45 degrees, the amounts to be added to \(r\) and \(g\) must be equal. If the other diagonal line \(Q_R Q_G\) through \(P\) coincides with the main diagonal \(R G\), then \(r + g = 1, b = 0\), and \(P_1\) must then be at \(P_Y\). All other positions on \(R G\) are transferred to the boundary lines \(R Y\) and \(G Y\), so that there is inevitably a discontinuity across the diagonal \(O Y\).

We consider the region below \(O Y\) where \(r > g\). The simplest way to achieve the requirement of filling the square is to set \(k = r + g\) and \(l = 2g\). \(P_1\) is then at \(P_2\), with the line \(Q_R Q_2\) parallel to the axis \(O G\). However, it seems desirable to reduce the amount of distortion as \(Q_R Q_G\) moves closer to the origin \(O\); a
simple way to achieve this is to multiply the amount added to \( r \) and \( g \) by a factor \((r + g)\), so that \( P_2 \) moves to the revised position \( P_1 \). A complementary argument applies to points on the other side of \( OY \), for which \( r < g \). Thus, we have

\[
\begin{align*}
\text{if } r > g, & \quad k = r + g(r + g), \\
& \quad l = g + g(r + g); \\
\text{if } r < g, & \quad k = r + r(r + g), \\
& \quad l = g + r(r + g);
\end{align*}
\]

(1) \hspace{1cm} (2)

Then \( K = nk \) and \( L = nl \).

Figure 2 illustrates the resulting colour distribution of the lookup table produced by equations (1) and (2). This square distribution doubles the number of possible \((K, L)\) coordinates, reducing the number of combinations of \( R, G \) and \( B \) that can equal any one \((K, L)\) coordinate. This is advantageous as it spreads the colours out more widely, allowing for better colour discrimination, especially the red, yellow and green which are important for the application to strawberry ripeness. The white point, at which \( R = G = B \), is at the position \( K = L = (5/9) n \). An effect of stretching the colour distribution into a square and rounding to obtain integer coordinates is that two blank regions exist, in the green corner where \( K = 1 \) and \( L = 210 \) to 254, and in the red corner where \( K = 210 \) to 254 and \( L = 1 \). These regions are close to where \( R = B = 0 \) and \( G = B = 0 \) respectively, so they have no effect on the functioning of the lookup table.

The advantage of using a 2D lookup table is that it allows a more comprehensive lookup than just using a one-dimensional lookup, e.g. using just the red value by itself or the CIELAB \( a^* \) value [10]. It requires less computational memory to hold than a three-dimensional lookup table [14] and from a user experience perspective is simpler to use, as manually defining and visualising a 2D region on a 2D table is easier than a 3D region on a 3D table.

2.4. Lookup table seeding and application

Each area that needs identification (ripe, unripe, etc.) is assigned a number. The numbers used in this study are shown in Table 1. The appropriate elements of the lookup table are then seeded with the area’s associated number. This seeding can be carried out either via manual selection of the appropriate elements, or by feeding a suitable seed image of a strawberry’s surface through equations (1) and (2) and allocating the assigned number to the element with the calculated \( KL \)-coordinate.

When using the seed image method, the locations of more than one area in the lookup table may overlap. In this case the elements in the overlapping regions are seeded with the sum of the numbers assigned to the areas involved. Assigning the numbers as in Table 1, or in a similar manner, means that each area, including the overlapping ones, is uniquely identified.

Additionally, the condition that \((R+G+B) > 3\) for a pixel in the seed image was implemented to prevent nearly-black pixels, e.g. those with \( R = 1 \) and \( G = B = 0 \), from being used in the lookup table. This was done to reduce the effect of noise in the seed image triggering false identification of areas when the lookup table was applied.

| Region | Ripe | Unripe | Ripe + Unripe | Calyx | Ripe + Calyx | Unripe + Calyx | Ripe + Unripe + Calyx |
|--------|------|--------|---------------|-------|--------------|-----------------|---------------------|
| Assigned Number | 1    | 2      | 3             | 4     | 5            | 6              | 7                   |

Table 1. Numbers assigned to each area

To use the lookup table, equations (1) and (2) are applied to all the pixels in an image of the strawberry under test. The image then becomes segmented into different areas based on where the original pixels are calculated to lie in the lookup table. The ratio of the segmented ripe to unripe areas provides a grading for the strawberry ripeness, i.e.
Estimated ripeness = Number of ripe pixels / Number of unripe pixels. \hspace{1cm} (3)

In the implementation demonstrated here, if a pixel is calculated as belonging to an overlapping region in the lookup table, it is ignored. For the unripe and calyx regions whose colours are similar and where substantial overlap is expected, ignoring the overlap between them will reduce the amount of false identification of calyx and leaves as unripe, resulting in a lowering of the estimated ripeness. Refinement of the regions may be carried out for example by applying a best fit algorithm to define continuous regions for each area.

2.5. Strawberry image samples
Strawberry images were acquired at an outdoor, commercial strawberry farm using a commercially available sensor. Lighting conditions were natural daylight with slight variations in intensity due to passing clouds, and sensor’s settings for white balance and exposure were left on auto. The strawberries were growing under polytunnels made of clear plastic sheeting in elevated trays organised into rows approximately 50 cm apart. To seed the lookup table, six strawberries with varying degrees of ripeness (Figure 4) were picked from a row and photographed. An image editor was used to crop the ripe, unripe and calyx areas of the photograph into separate images (Figure 5).

Subsequent photographs of strawberries growing on the plants outdoors were taken over the course of a few hours. Ten suitable strawberries from the photographs were chosen and cropped, and were used as test images for the colour lookup table method.

Figure 4. Six strawberries selected from the rows of trays.
3. Results and discussion

3.1. Daylight lookup table
The lookup table seeded with the images in figure 5, with each area colour-coded, is shown in figure 6. The three primary areas, ripe, unripe and calyx, exist in distinct locations in the table. Some overlap is seen between these three areas. The overlap between the unripe and calyx areas is larger than that between ripe and unripe due to their greater similarity in colour. Stretching the lookup table into a square has the beneficial effect of reducing the percentage area of “Ripe + Unripe” region from 7.4% of all occupied (K, L) coordinates to 4.2%, allowing for better discernment between ripe and unripe. Here we used the lookup table as it stands. Further improvements such as refining the shapes of the regions with a best-fit algorithm and better handling of overlapping regions are not implemented in this study.

3.2. Image segmentation with lookup table
Figure 7 shows ten images of strawberries captured at the commercial farm with a complete range of variation in ripeness and colouration. The images contain only isolated berries to ensure only a single object is analysed per image.

Examining images 1, 2 and 9 in figure 8, the lookup table successfully segments the ripe areas. In images 7 and 8 where the strawberry has both ripe and unripe regions, both areas are also clearly defined. Unripe areas are also identified correctly in most of the test images, with the exceptions of 4 and 6,
where the strawberries are highlighted as being part of the overlapping unripe and calyx region of the lookup table. This region of the lookup table also has a small effect on the detection and segmentation of the calyx areas, seen in image 1. In images 8 and 9 there are calyx areas that are unsegmented due to their colours lying outside the calyx region defined in the lookup table.

Ideally images presented to the ripeness method presented in this paper will contain a single berry and this requires a good shape identification method from the computer vision system. However, in practice, some background and extraneous features will also appear in the image frame. Analysing these non-berry components in the images, it is apparent that the lookup table identifies much of the background as being unripe (green), calyx (blue) or both (purple). As the images were taken while the strawberries were still attached to the plant, this is expected because much of the background will be leaves, grass or other unripe strawberries. Grey plant supporting trusses and rope used at the test farm is segmented as unripe, due to its ratios of the \((R, G, B)\) values. Finally, in images 1 and 3, black plastic lining is picked up as a ripe area due to the specific ratio of red to green and blue in the pixels. Some of these problems could possibly be reduced by ignoring dark pixels, during the seeding of the lookup table.

![Figure 7. The cropped strawberry images used to test the lookup table method.](image-url)
3.3. Ripeness measurement

The calculated ripeness’s presented in Table 2 show that the lookup table method reliably classifies the strawberries into two classes. The four ripe strawberries have values greater than 0.5 and the four unripe strawberries have values below 0.5, which compares favourably with previous works using colour cameras [10], multispectral cameras [11] and hyperspectral cameras [9, 12]. However, the accuracy of the ripeness determination is reduced in some images due to incorrect segmentation of background features, seen in the values obtained for images 1 and 2 compared to 5 and 9.

Table 2. Estimated ripeness of the strawberries shown in figure 7 and figure 8.

| Strawberry | State      | Estimated Ripeness |
|------------|------------|--------------------|
| 1          | Ripe       | 0.58               |
| 2          | Ripe       | 0.57               |
| 3          | Unripe     | 0.11               |
| 4          | Unripe     | 0.00               |
| 5          | Ripe       | 0.82               |
| 6          | Unripe     | 0.00               |
| 7          | Semi-ripe  | 0.52               |
| 8          | Semi-ripe  | 0.67               |
| 9          | Ripe       | 0.84               |
| 10         | Unripe     | 0.05               |

Improvements in algorithm ripeness estimation could be achieved by manual image cropping to select only the berry, which for a fully automated system would require accurate shape identification, an area which is well developed but out of scope in this work. Similarly, other ripeness detection methods have not dealt with extraneous features in the images as typically harvested strawberries were placed on a uniform colour background [9-12]. Improvements to the coordinates of lookup table can be refined through machine learning as large numbers of samples are processed in a real environment.

Figure 8. Images from figure 7 segmented using the same colour scheme as defined in figure 6.
The regions in figure 6 are bounded approximately by straight lines radiating from a point near the central white point. This suggests that an adequate table with solid blocks of values could be constructed, based on the seeded one. Equivalently, the $K$ and $L$ values could be segmented numerically by evaluating $(L - L_0) / (K - K_0)$, where $(K_0, L_0)$ are the coordinates of the origin point.

The demonstrated work uses the lookup table in a static fashion, with the regions defined from a single image taken under one set of lighting conditions. Further work would be needed to adapt the system to be used robustly under the varying daylight conditions experienced at an outdoor farm.

4. Conclusions

In this paper we have presented and demonstrated the use of a 2D colour lookup table to segment a strawberry image and use the ratio of unripe to ripe areas to estimate strawberry ripeness. Using images taken at a UK outdoor strawberry farm, the lookup table was seeded so that regions for ripe strawberry, unripe strawberry and the strawberry calyx were defined. Testing sample images of unripe, half-ripe and ripe strawberries has shown that the approach is viable. The four ripe strawberries in the sample were all calculated to have ripeness estimates greater than 0.5, while the four unripe strawberries gave estimates less than 0.5. The estimates were found to be highly affected by the presence of background features in the sample images, which were primarily misidentified as unripe regions. Suggestions on how to refine the regions of the lookup table are given as well as extensions for real-time use more appropriate for outdoor application.

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