RECOGNITION ALGORITHMS FOR DETECTION OF APPLE FRUIT IN AN ORCHARD FOR EARLY YIELD PREDICTION

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ABSTRACT

The challenge in perennial fruit cultivation is estimating the number and diameter of fruit on a tree as early as possible to achieve yield estimates for farm operations, fruit trade, retailers and storage facilities. Apple recognition algorithms based on colour features are presented to estimate the number of apple fruits and develop early predicting models of apple yield. Fifty cv. 'Gala' apple digital images were captured twice on one, the preferred Western side of the tree row with a variability of between 70 and 170 fruit per tree, under natural daylight conditions at Bonn, Germany. An apple recognition algorithm with colour difference R-B and G-R was developed for apple images after June drop, and two different colour models were used to segment the ripening period's apple images. The algorithm was tested on 50 images. A close correlation coefficient R^2 of 0.80 was obtained between apples detected by the fruit counting algorithm and those manually counted. Two sets of data were used for modelling yield prediction of the apple fruits. In the calibration data set, the R^2 value between apples detected by the fruit counting algorithm and actual harvested yield was 0.57 for young fruit after June drop. In the validation data set, the R^2 value between the number of apples predicted by the model and actual yield at harvest was 0.58. The proposed model shows a great potential for early predicting yield for individual trees in an orchard. The present results on apple may be applicable to many other fruit crops like Citrus, pear, peach, apricot, kaki, nectarine and almond.

Keywords: Apples, colour, fruit crops, modelling, yield prediction

INTRODUCTION

Annual fruit production is 550 – 580 mil tons worldwide. Fruit trees are naturally subjected to alternate or biennial bearing. This change between years of high and low yields is often due to adverse weather conditions such as late spring frosts or hailstorms, which destroy the flowers or fruits, and then continues throughout the lifetime of a fruit tree (Untiedt and Blanke, 2001). Both the US and Europe produce 10 mil tons of apples each year, with up to 20 % fluctuations; these 2 mil tons translate into 600 mil € euros or 700 mil US $ dollar (Blanke, 2011); similar values can be obtained for other fruit crops.

So far, yields prediction has concentrated on annual arable crops rather than perennial crops. The few papers on perennial fruits crops e.g. apple (Bulanon et al., 2002; Stajnko et al., 2009; Wachs et al., 2010), pear (Perry et al., 2010) or Citrus (Chinchuluun and Lee, 2006) reported yield estimation at harvest (based on colouration), when the fruit are already fully coloured and nearly ripe. Bulanon et al. (2002) recognized ripe, fully-grown dark-red cv. ‘Fuji’ apples for robotic harvesting in October in images using a $YC_RC_GC_B$ colour model, in which red colour was employed as the feature to segment red apples from the background such as green leaves.

However, the challenge in perennial fruit cultivation is estimating the number and diameter of fruit on a tree as early as possible after June drop, when a large and variable but unpredictable amount of fruit may drop, which varies from year to year (Winter, 1986). This may have been one of the reasons why one approach of yield prediction at the flowering stage gave poor results of 18 % accuracy of predicted yield (Aggelopoulou et al., 2011). Recognizing fruits in an apple tree is the first step in estimating the number of fruits for yield prediction. Yield prediction in fruit orchards would enable precision agriculture in terms of in-time estimates of volume flows of fruit, leasing of fruit bins, planning storage space, fruit store management, labour hire for fruit picking, booking grading facilities and transport equipment as well as trade and retail orders three months ahead of harvest (Blanke, 2011).

The objective of this study linking image processing with agricultural engineering and horticultural research was to develop algorithms to estimate the number of green unripe fruits or those with low red partitioning for single trees at a time, when fruit are small green and still attached and have to be discriminated against green leaves under natural daylight conditions.

MATERIAL AND METHODS

Site description, image acquisition, image processing and fruit counts

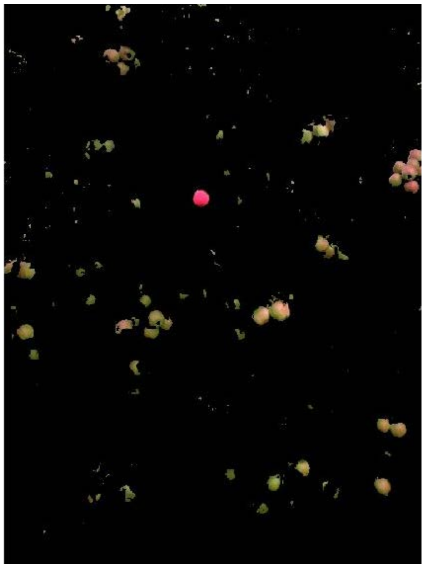
Nine-year-old cv. ‘Gala’ apple trees, trained as slender spindles and spaced at 1.5 m x 3.5 m at Campus Klein-Altendorf, University of Bonn, Germany, were mechanically-thinned at 360 rpm (rotations per minute) and 420 rpm (Damerow and Blanke, 2008), or left un-thinned to produce between 70 and 170 fruits/tree. One image of each of 50 apple tree canopies was acquired on July 17th 2009, when fruit were light-green after June drop. Since (apple) fruit trees are planted universally in a N-S orientation to optimise light utilisation, digital images were taken on the preferred western side of the tree row, which captures the long afternoon sun and grows the majority of class I fruit. These digital images were captured in ‘auto-focus’ mode (without use of the zoom) at 1.5 m height and at constant distance of 1.4 m perpendicular to the tree row in natural daylight using a commonly available digital camera with 1,704×2,272 pixels. A red calibration sphere was placed in the top of the tree, which resembled the size of the apple fruit and was used to determine fruit size. Photography conditions were diffuse light. Images were uniformly resized to 512×683 pixels to improve the data processing speed and analysed using Matlab (version 7.0.1, Mathworks Inc., USA). After harvest, fruit were sorted using a commercial grading machine (type MSE2000, Greefa, Geldermalsen, Holland) to provide yields/tree and final fruit counts per tree.

RESULTS

Image processing algorithm

Figure 1 shows images taken on July 17th 2009 after June drop (Fig. 1). A white drapery was placed behind the target trees, as shown in Figure 1a, in order to distinguish fruits from the background including leaves, branches and sky, and to count the number of fruits, the first two steps to segment an apple tree image; size calibration was based on the red sphere. After June drop, colour of the cv. ‘Gala’ fruit was turning from green to red, whereas it was completely red during the ripening period.

(a) Original digital photograph with the red calibration sphere against a white drapery as background



(b) Apple fruits segmented from the background

(c) Binary images after removing noise

Fig. 1. Original digital photograph (1a) and results (1b, 1c) of the image-processing algorithm for the June drop period

Fruit recognition algorithm for the early developmental stage after June drop

Figure 1a shows an apple fruit image taken in natural daylight condition after June drop, where a threshold has to be determined to segment apple fruits from the background (leaves, branches and sky) in an image.

The black line in Figure 2a intercepted an apple fruit, leaves and branches in an apple tree image after June drop. Figure 2b provides RGB colour values of this black line in figure 2a as Y-axis, while the X-axis gives the pixel number. The red value R was larger for the apple fruit compared with the background (leaves and branches) and larger than the blue value B, while the value of colour difference R-B varied between 90 and 110 (Fig. 2b).

Correction procedure for potentially falsely identified fruit

The RGB values of the profile line in figure 2a was used to segment apple fruit from the background. The majority of apple fruits in an image could be segmented from the background at a threshold colour difference R-B of 40. If (R-B) < 40, the RGB colour values of this pixel are set to zero, equivalent to black colour; otherwise the original RGB colour values of this pixel remain (Fig. 2b).

If { $R - B > 40$ } => apple fruit
If { $R - B \leq 40$ } => background

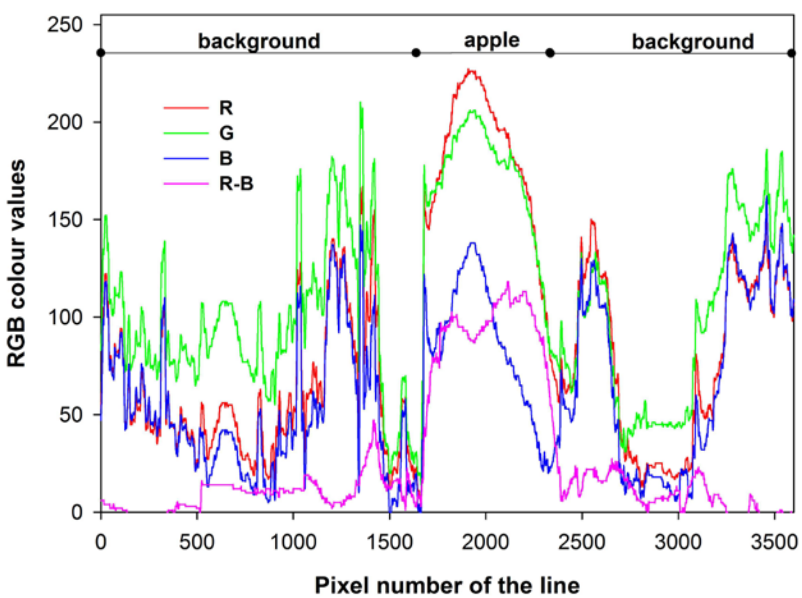
However, some leaves and branches were first falsely classified as fruits due to uneven, patchy or irregular illumination and/or mutual shading. In this case, apple fruit pixels and falsely classified background (leaves and branches) pixels were categorised as one of three classes, apple fruit, leaf or branch. In particular, upward curved leaves, exposing their light green lower (abaxial) side resembled the light green colour of the young apple fruits. Through calculating and analysing R, G, B colour values for each class, a threshold for the colour difference G-R between apples and a falsely classified background was detected:

If { $G - R < 20$ } => apple fruit

If { $G - R \geq 20$ } => falsely classified background

The colour difference G-R of pixels belonging to the leaves and branches, which were falsely classified as fruits, exceeded 20, whereas it remained below 20 for the apple fruit pixels. Therefore, the thresholds of colour difference R-B (40) and G-R (20) were combined to segment apple fruits from the background; the result of this processing step was shown in Figure 2b.

(a) RGB image with black line for subsequent profile analysis



(b) Line profile map

Fig. 2. Colour analysis (RGB) of the line in figure 2a from a typical apple tree canopy image after June drop

In figures 1b, apple fruits were segmented from the background. There were still some leaves and branches, which were falsely recognized and formed the noise. In order to remove noise and process binary images, the following image pre-processing operations were performed: 5 * 5 pixel median filtering, morphology operation of opening and closing with 2 * 2 circular structuring element to remove circle noise with the area of pixels below 2 * 2 circular structuring element, and fill the gaps in the binary image (Fig. 1c). The different steps employed in the image processing are visualised in a flowchart (Figure 3).

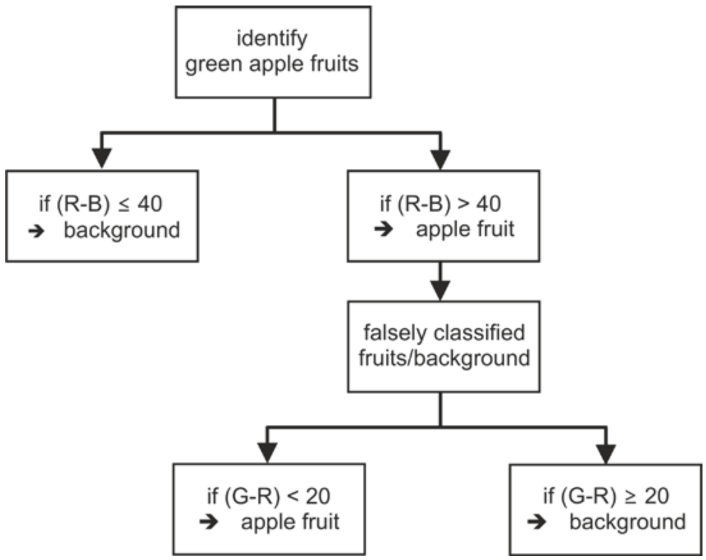


Fig. 3. Flowchart explaining the different steps of discrimination

Fruit counting algorithm

For estimating the number of apple fruits in an image, the connected fruit pixels were considered as a single connected domain. The total number of connected domains was considered as the number of apple fruits in the image. However, the connected fruit pixels in the processed image included a variety of different apple configurations. These can be grouped into one of three configurations: 1) a single apple fruit, 2) two or more apple fruits, which were connected with each other and formed a fruit cluster and may contribute to under-estimation of the fruit number, 3) at least one apple fruit, which was partly obscured by leaves and separated into different connected regions in an image and may contribute to over-estimation. To solve these problems, the area feature of each connected domain was extracted in each image to modify the under-estimation and over-estimation of the fruit number. The connected domain area of two or more apples was compared with the pixel proportion of the bright red calibration sphere (Figure 1a), which was of commensurate size to an apple fruit in July. The following modifications were made in the fruit counting algorithm: If the area of a connected domain exceeded 400 pixels (20 x 20 pixels= size of red calibration sphere), the number of these connected domains was doubled, i.e. fruit clusters with a large size were assumed to be two apple fruits not one. Alternatively, if the area of a connected domain was less than 30 pixels, the number was halved and the two small, connected domains considered as one apple fruit. The reason why the fruit clusters were counted as two instead of one or merely combined the two small areas into one was that it was difficult to define a threshold in areas of overlapping apple fruits.

DISCUSSION

Assessment of fruit counting algorithm

A linear regression analysis was conducted for each image of an entire tree for 50 apple trees. From the images, the number of fruits per tree assessed by a fruit counting algorithm was correlated with manual fruit counts by two people. This approach was used to evaluate the performance of the fruit counting algorithm employed in the present study. The coefficient of determination was R^2 = 0.80 after June drop (Fig. 4). Images with a large number of apples obscured by leaves or overlapping fruit in a fruit cluster resulted in a discrepancy between the fruit numbers detected by the fruit counting algorithm and those manually counted. To overcome this discrepancy, a more advanced algorithm was developed to segment overlapping apples in an image.

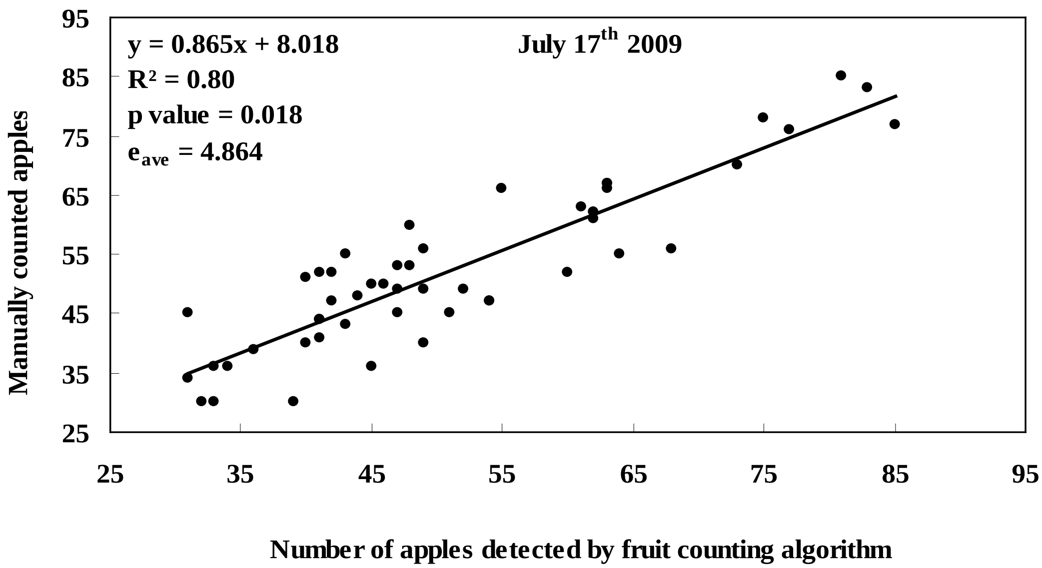


Fig. 4. Regression analysis between apples detected by fruit counting algorithm and manually counted in the image after June drop (r^2= 0.8)

Prediction of the apple yield after June drop

Thirty randomly chosen apple images of each period were divided into two sets of data. One data set was used to correlate the fruit detected by the counting algorithm with the fruit number of each tree at harvest; the other data set was used for validation of this correlation.

Yield prediction using the fruit counting algorithm and actual yield were correlated using linear regression analysis for the calibration data set for the early period after June drop (Fig. 5). A correlation coefficient of R^2=0.58 was achieved, which was acceptable considering that a) images were deliberately only taken on the western side of the tree, b) this early stage of 3 months before harvest and c) potentially obscured fruit with their small size in the canopy. Fig. 7b shows a regression analysis between the calibration and validation data sets. A correlation coefficient of R^2=0.58 was achieved for this regression between the yield estimated by the yield prediction model and actual harvested yield with an RMSE of 24 fruits/tree (Fig. 6b) of trees bearing up to 150 fruits per tree (16% inaccuracy). These results suggest that the prediction model developed in the research could have potential for early estimation of the fruit yield under natural light conditions with as little as only one image per tree at this ‘difficult-to-estimate’, early, post-June drop stage.

Prediction of the apple yield during fruit ripening

A similar regression analysis was conducted for the apple ripening period, as shown in Fig. 5. A closer correlation (R^2=0.70) was obtained when relating actual harvested apple fruit to a set of apples detected by the fruit counting algorithm, as shown in the linear graph in Fig. 5. The increase in the correlation coefficient during the fruit ripening period was attributed to the closer time to the apple harvest and the obvious colour and diameter changes of apple fruits, which could be detected more easily based on colour features of image processing.

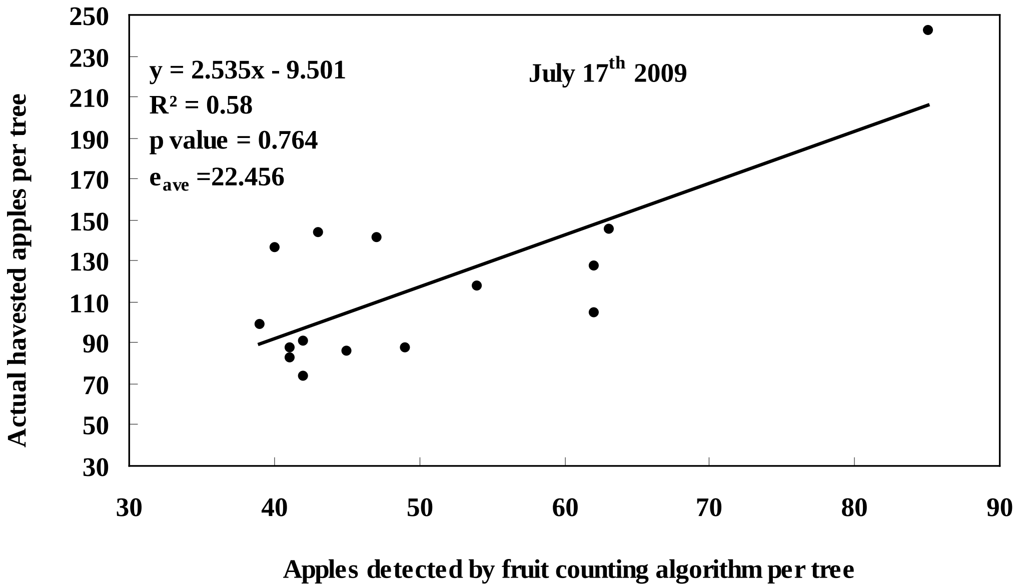


Fig. 5. Prediction model for the June drop period showing the regression between detected and fruits harvested 3 months later (r^2=0.58; p value 0.764)

Some fruits, partially obscured by leaves and other adjacent or overlapping fruit, also adversely affected the accuracy of the fruit counting algorithm. An automatic counting algorithm could facilitate detection of partially obscured fruits or split the fruit cluster based on edge detection or some other features such as shape or texture.

With the algorithm being sufficiently improved, an early yield prediction based on image processing technology could be applied to an apple orchard. These software tools could be implemented e.g. in the design of a tractor-based (autonomous) automated system or OTR (over the tree), which moves through or over the tree rows in an orchard of any type of fruit. This system would provide digital photos of a defined resolution, preferably in any daylight conditions without artificial illumination (flash), for precise information on fruit set. This work is a step to identify and overcome possible errors and develop thresholds in these algorithms.

The present approach based on image processing differs from thermal imaging (Stajnko et al., 2004) to estimate the number of apple fruits on the basis of temperature gradients between fruits and their background. This approach was associated with difficulties in detecting fruits and leaves deeper in the tree canopy and has not been further pursued. The authors then used texture-based fruit recognition (Rakun et al., 2011). Our approach also differs from that of Wachs et al. (2010), where two camera systems (thermal and colour image) had to be employed to recognise 53-74% of fully-grown, full-size ripe cv. 'Golden Delicious' and 'Granny Smith' apple fruits in order to count fruit numbers per tree in Israel. Other approaches in terms of fruit crops and techniques include citrus, where colour segmentation and marker-controlled watershed algorithms were used to estimate the yield of mature orange-red citrus fruit (Bulanon et al., 2009) and did not include young, small, light-green citrus fruit.

CONCLUSIONS

Two fruit recognition algorithms were developed for each of the two fruit development periods, young, small green fruitlets and mature red apple fruits, based on colour features to estimate the number of apple fruits in an image. Fifty images were taken of 50 trees with a commercial digital camera during the two developmental phases from one side of the trees under natural light with a white drapery as background and a red calibration sphere. Variability was induced by three levels of blossom-thinning trees to achieve 70 to 170 fruit per tree. Numbers of fruits per tree assessed by the fruit counting algorithm and manually counted fruits in both periods were correlated with R^2 values of 0.80 and 0.85. In the fruit ripening period, a closer correlation between the number of fruits assessed by the recognition algorithms with actual fruit yield (R^2=0.70) was achieved. Actual and predicted apple yield were also closely correlated (R^2=0.71). This approach may also be suitable to other bi-coloured fruit crops like apricot, peach, nectarine and citrus fruit; the algorithms used for the first "June-drop period" may also be suitable for single-coloured fruit, which remain green during maturation.

Successful fruit recognition in an orchard would enable determination of single tree yields at an early stage of fruit development several months before harvest. Early and accurate yield prediction would have large benefits for precision agriculture; apple producers would have better control of economics, production, harvest management (hire of labour and bins) and storage capacity. Site-specific management would also be better implemented, if yield prediction information were available. These results showed great potential of the models for early prediction of apple yield.

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