

Automated blossom detection for precision fruit farming

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INTRODUCTION

In arable farming, an ongoing trend is increased availability of data about crops that can be used in optimisation of different crop care practices. Our ‘Fruit 4.0’ project aims to apply similar technologies in orchard systems in order to optimise current farming practices. In this paper, we address the topic of blossom detection in apple trees.

Apple trees have the tendency to produce an overload of blossom, having a negative effect on fruit quality and yield. To overcome this effect, currently uniform chemical thinning is applied on orchard sections, although there is a great variation in the number of blossoms per tree within that orchard. To apply tree specific chemical thinning, a robust system is required that determines the blossom load on a tree. To determine blossom load on trees, a recording setup was realised, classification algorithms were developed, and field experiments were done to evaluate the practical performance.

MATERIALS AND METHODS

In order to reach a reliable method of determining the blossom load per individual tree, a measurement system was build and a classification method was tested. Both were first established in 2017 and adjusted according to the first findings in 2018. For the experiments, a single row of interest was selected in the experimental orchard of the Proeftuin Randwijk, this row contains 99 trees (Elstar), planted at a 1.10 m tree spacing (3 m row width), in a north-south orientation.

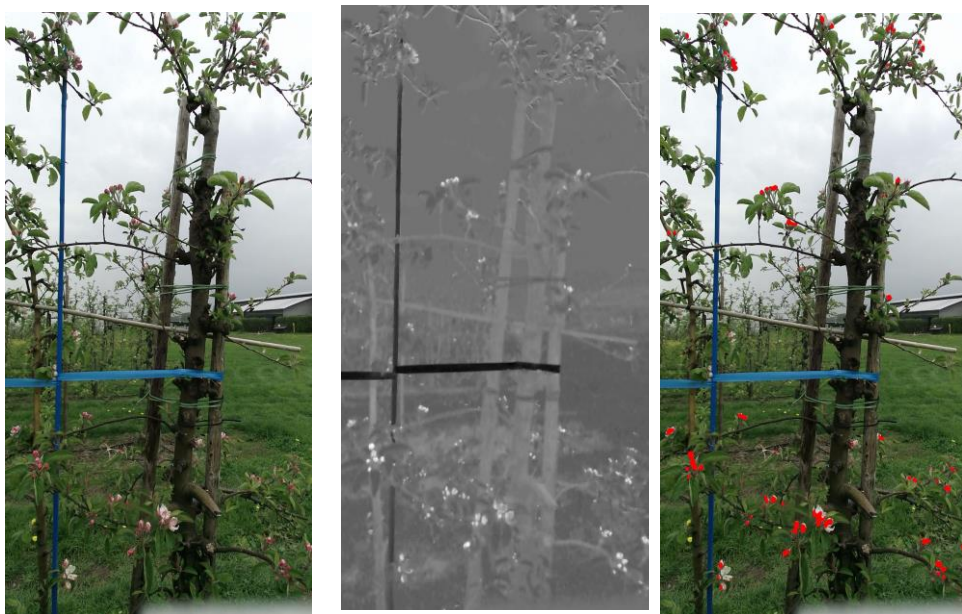


Figure 1 (left): colour image, (middle) Cr component of colour image, (right) colour image overlaid with segmented blobs.

We initiated experiments in 2017, before the blossoming period. The measurement setup consisted of a single Microsoft Kinect One camera, taking images at 2Hz, driving at about 2 km/h, RTK-GPS positions were logged at 10 Hz and in a later stage matched to the images by timestamp. For the 2017 dataset, a classic segmentation method was performed, in which a colourspace transformation was used to highlight the pink component of early apple blossom. The best colourspace transformation in which the early apple blossom stood

out was the Cr component of the YCbCr transformation. Figure 1 shows that in the Cr image, the regions where the flowers are present are noticeably brighter than the surrounding regions. We therefore apply an adaptive threshold to select those pixels which are at the 99th percentile, or the top 1% of the histogram of the Cr image. This pixelwise segmentation is shown overlaid on the colour image in figure 1.

In 2018, the measurement setup was improved according to the lessons learned in 2017. First of all, three Intel Realsense D435 cameras were installed to generate a higher resolution, capturing a section (top, middle, bottom) of the trees each and to ensure whole tree recording. So there was a higher pixel density for the blossom segmentation. Secondly, the recording frequency was increased to 6 Hz, to increase recording speed to 3.6 km/h. The 2018 dataset for classification algorithm development consisted of two measurement days. One at the pink bud stage (BBCH57) and one at stage where most of the blossom clusters are open BBCH 65. In accordance with the first findings of the research, the first dataset will be used for further analysis, since the pink outer leaves are better distinguishable.



Figure 2. Detection performance developed bud detection system on 2 test images. Pink squares contain the detections.

In order to get the number of blossoms at high enough speeds for real time processing, the YOLOv3 convolutional neural network was selected to do the image segmentation. Metrics for evaluation of the system were the F1-score, precision, recall and the counting error, which is the error between ground-truth flower bud count and predicted flower bud count. In figure 2, an indication of classified apple blossoms can be observed.

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RESULTS AND DISCUSSION

In the 2017 colourspace transformation method we were able to classify about 80 % of the visible blossom cluster pixels correctly. Even though this is a promising number, we found that the classification was too specific for this specific situation. The method would need to be re-developed before it could be applied to another situation.

The results for the 2018 YOLOv3 method show that the developed system is able to detect objects within the required processing time, 0.03 seconds. 50% of the flower bud count estimations per picture are within the required error range of 10 flower buds, for a range of 20 flower buds, 80 % of the images are classified in range. The F1-score, precision and recall were respectively 0.63, 0.65 and 0.61 which means that 65% of the detections was a flower bud and 61% of the annotated flower buds was detected.

The model was able to detect flower buds on unseen data, captured with another camera and in another year, with a maximum F1-score of 0.49, a precision of 0.45 and a recall of 0.53. These numbers are lower than the ones observed with the data of interest, however, they do show potential for when the model is trained for a more diverse dataset.