Supplementary Material - S^{3}AD: Semi-supervised Small Apple Detection in Orchard Environments

Robert Johanson*, Christian Wilms*, Ole Johannsen, and Simone Frintrop
Computer Vision Group, University of Hamburg, Germany
* denotes equal contribution
{firstname}.{lastname}@uni-hamburg.de

This supplementary material includes details on the automated apple property annotation in our dataset MAD (see Sec. 1), details about the training of our TreeAttention module in Sec. 2, and a description of the tile selection process for the semi-supervised training of S^{3}AD's detector (see Sec. 3).

1. Apple Property Annotations in MAD

As briefly mentioned in the main paper, we automatically annotate the apple instances with three properties. Details about the annotation process regarding the properties as well as statistics on the properties are presented below.

1.1. Relative Size

The relative size of an annotated apple instance is directly calculated based on the annotated bounding box. It is defined as the area of the bounding box over the area of the image, which is 3840×2160 for all images in MAD. Hence, the relative size is a value between 0 and 1. Measuring relative size in contrast to absolute size makes this property comparable to other datasets, since images are usually resized at the input stage of object detection systems.

Figure 1a shows the distribution of relative sizes in the test split of our dataset MAD. It is clearly visible that most apples have a relative size below 0.001, resulting in an absolute area below 91^2 pixels in MAD's high-resolution images. Above this level, only a few annotations (8.4%) exist, which indicates a strong focus of MAD on small apples.

1.2. Occlusion

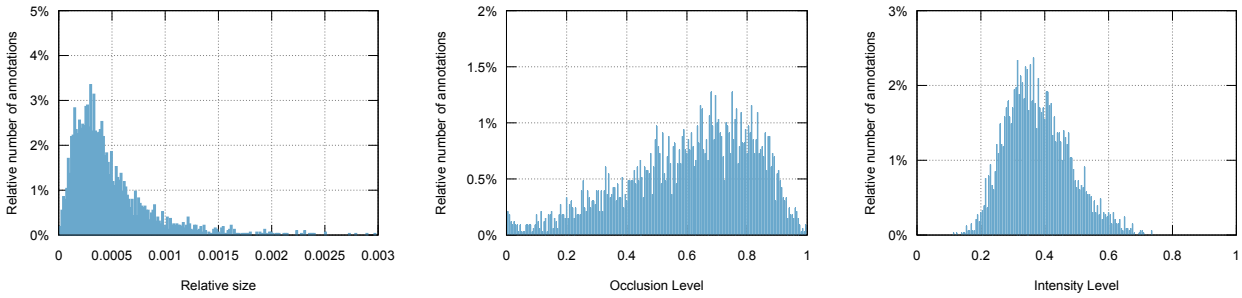
The level of occlusion is measured as the portion of an annotated bounding box depicting the actual apple. To estimate this area, we use the domain knowledge that the apples in our dataset are primarily red, while the occluders (mostly leaves and branches) are green or brown. Therefore, we estimate the hue of the apples by taking the peak hue value (HSV color space) across all pixels of annotated apples in MAD. Subsequently, we apply binary segmentation within each annotated box using the peak hue with some margin. All pixels within each box that are close to the determined peak hue value comprise the actual apple, while the remaining pixels show background areas or occluders. An example of this segmentation is visible in Fig. 2, where green pixels denote estimated occluders within each annotated bounding box. Since we measure the portion of an annotated bounding box depicting the actual apple, the range for the level of occlusion is $0, \ldots, 1$. Here, 0 represents full occlusion, while 1 represents no occlusion.

The distribution of the occlusion levels is depicted in Fig. 1b. From the figure, it is visible that only a few annotated apples are almost occlusion-free (occlusion-level > 0.9), which is also related to the automatic annotation process that counts the corner areas of the bounding box that do not cover apple areas as occluders. Apart from this effect, most apples (84.2%) are moderately occluded, with an occlusion level between 0.3 and 0.9. Severe occlusion with less than a third of the apple being visible only occurs on 10.9% of the annotated apples. This is also related to the difficulty these apples pose for manual annotation.

1.3. Lighting Conditions

Similar to the relative size, we directly derive the lighting conditions from the annotated bounding box. We define the lighting condition as the mean intensity level of the annotated bounding box in the HSV color space. Hence, the lighting condition measures if an annotated apple is dark and in the shadow of a leaf, or directly in the sun and much brighter. Similar to the previous measures, the range for the annotated lighting condition is $0, \ldots, 1$.

Figure 1c shows the distribution of the intensity values as a surrogate for the lighting conditions across MAD's test split. While most apples are well illuminated, there is a general tendency of the distribution towards darker intensities. This indicates that a relevant amount of apples is in the shadow of leaves or other parts of the tree. The fact that almost no annotated apples are very bright or dark is not surprising. Very dark apples are also very difficult to spot



(a) (b) (c)

Figure 1. Distribution of values for each of the three properties annotated in our dataset MAD.

(a) Base image (b) Estimated occlusions

Figure 2. Test image of our dataset MAD (a) and visualization of estimated occlusions (b). Red pixels denote visible parts of apples, while green pixels denote estimated occluders.

Table 1. Pairwise Pearson correlation coefficients ($p \leq 0.05$) of the different properties annotated in the test split of the dataset MAD.

	Size	Occlusion
Lighting	0.088	0.370
Occlusion	0.034	

for human annotators, while very bright apples only appear in extreme settings with strong overexposure.

1.4. Relation Between Properties

Besides the above-mentioned statistics on the individual properties, we also studied the relation between the attributes to show that they measure different attributes of the annotated apples. To discover possible relations, we compute the Pearson correlation coefficient between each pair of properties across all annotated apples of MAD's test split. From the results in Tab. 1, it is clearly visible that no strong correlations exist. The weak correlation between occlusion and the lighting conditions is due to the way of measuring the lighting conditions. If an apple is substantially occluded by, e.g., a leaf, the leaf will dominate the lighting conditions. Overall, the results show that all properties measure different aspects of our data.

2. Training Details of TreeAttention

For training TreeAttention, we utilize the alpha shapes generated from the bounding boxes of the 66 annotated training images in MAD. To save computational resources, we downsample the input image to 512×288, which will not impede the results, since TreeAttention is only used for a rough localization of the tree crown. As a loss function, we apply binary cross entropy loss and learn for 50 epochs with an initial learning rate of 0.0001, early stopping, and RMSprop optimizer.

3. Unlabeled Image Tile Selection for Training

For training S^3AD's detector in the semi-supervised Soft Teacher framework, we select unlabeled image tiles from the 4,440 unannotated images in the train split of our dataset MAD. This is done to avoid the large number of unlabeled image tiles that would only feature background without any apples. The unlabeled image tiles are selected by generating an attention map for each unlabeled image with TreeAttention. TreeAttention is applied to the unlabeled images as described in Sec. 4.1 of the main paper, with the only difference being that the attention map is binarized with a threshold of $\tau = 0.5$, and a tile is only selected if it intersects at least 50% with the binary mask. Hence, the selection of the tiles is stricter than in the main approach to ensure minimal false positives.