Prediction of the vigor and health of peach tree orchard

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Abstract. New technologies are a great support for decision-making for agricultural producers. An example is the analysis of orchards by way of digital image processing. The processing of multispectral images captured by drones allows the evaluation of the health or vigor of the fruit trees. This work presents a proposal to evaluate the vigor and health of trees in a peach orchard using multispectral images, an algorithm for segmentation of trees canopy, and application of vegetable indexes. For canopy segmentation, the Faster R-CNN convolutional neural network model was used. To predict the health of the peach trees, the vegetable indexes NDVI, GNDVI, NDRE, and REGNDVI were calculated. The values of the NDVI, GNDVI, NDRE, REGNDVI indexes obtained for the healthiest tree were 0.94, 0.86, 0.58, and 0.57, respectively. With the application of this method, it was possible to conclude that the use of multispectral images together with image processing algorithms, artificial intelligence, and plant indexes, allows providing relevant information about the vigor or health of the cultures serving to support the decision making in agricultural activities, helping the optimization of resources, reduction of time and cost, maximizing production, facilitating the work of agricultural explorers.

Keywords: Image processing, Health, Vigor, Canopy segmentation, Vegetation indexes, Faster R-CNN, Multispectral images.

1 Introduction

Modern agriculture is increasingly dependent on systems based on new technologies, which involve robotics, image processing, remote monitoring, and even artificial intelligence in the development of methods to support decision-making and use of information relevant to the evolution of agriculture [1].

There have been many efforts to move beyond species assessment to functional aspects of vegetation condition. Vegetation condition is the measure of vegetation response to stress. Good condition is associated with green, photosynthetically active vegetation, while stressors such as water and nutrient deficiencies or pest infestations result in low or poor condition. Physiologically, plants respond to stress by reducing chlorophyll activity and subsequently producing other pigments. These responses can be measured in the remote sensing signal in both visible and near infrared (NIR) [2]. There is a strong correlation between vegetation composition, structure, and function and signatures observed by remote sensing instruments. These remote sensing systems can be used to identify and map a variety of phenomena, including small to large variations in the characteristics, health, and condition of vegetation across a landscape [3].

Remote sensing data from satellites and airborne sensors typically have large coverage areas and are highly dependent on the constellation of viewing and illumination angles and atmospheric conditions [4]. To address these issues, the application of UAV-based multispectral image data is used to assess vegetation condition in-situ, rather than using remote sensing data. The vegetation index is generated from combinations of two or three spectral bands (red and near-infrared being the most used), whose values are summed, divided, or multiplied to produce a single value (index) that can be used as an indicator of the amount of vigor of vegetation [5].

To calculate vegetation indexes it is necessary to delineate the area of interest, i.e., canopy areas, which can be supported by a computer vision method.

There are several traditional methods of segmentation of manually performed hearts. Unlike those commonly used, this job requires an artificial intelligence method of image segmentation called Faster R-CNN (Faster Region-based Convolutional Neural Network) [6]. This model, contrary to the traditional and commonly used, has as main difference and advantage relating to the obtaining of vectors, based on the characteristics of images automatically and optimized. In addition, a vegetation index, such as the Normalized Difference Vegetation Index (NDVI), is used to evaluate peach trees.

2 Related Work

Several studies have been conducted in this sense. Underwood et al. [7] developed a mobile terrestrial "scanning" system for almond orchards, capable of mapping the distribution of flowers and fruits and predicting the productivity of individual trees. By stifling the canopy volume and studying the images taken by the terrestrial mobile vehicle that examines either the orchard and registered the data of the LiDAR (Light Detection and Ranging) sensor and camera sensors, it is possible to estimate the density of flowers and fruits. They evaluated 580 fruit trees at peak flowering, fruiting, and just before the rabbit hutch for two subsequent years where the canopy volume had the strongest linear relationship with the production with R2 $1/4 = 0{:}77$ for 39 tree samples in two years. Hunt Jr. et al. [8] evaluated the Triangular Greenness Index (TGI), developed to be sensitive to the chlorophyll content of the leaf, applying nitrogen during vegetative growth to avoid yield losses, but only the portions with severe nitrogen deficiency (very low chlorophyll content) were discoverable. In this case, they concluded that the TGI may be the spectral index by which digital devices mounted on low altitude aerial platforms can be used for a low-cost assessment of fertilizer needs. In order to contribute to this research topic, this paper evaluates the vigor and health of peach trees using multispectral images in a Faster R-CNN convolutional neural network algorithm for segmentation of trees canopy, and the calculus of vegetable indexes (NDVI, GNDVI, NDRE, and REGNDVI) to predict the health of the peach trees.

3 Materials and Methods

3.1 Multispectral Camera

The Micasense RedEdge-MX multispectral camera shown in Fig. 1 was used to acquire the images. This camera simultaneously captures five discrete spectral bands Blue (B), Green (G), Red (R), Red Edge (RE), and near-infrared (NIR). In general, these images (5 bands) are used to generate accurate and quantitative information on cultures [9] [10].

Fig. 1. Micasense RedEdge-MX multispectral camera.

This camera weight around 230 g and has dimensions 8.7cm x 5.9cm x 4.54cm, being suited to be mounted on drones. The sensor acquires the spectral bands in the following Wavelength (nm): Blue: 475 nm center, 32 nm bandwidth; Green: 560 nm center, 27 nm bandwidth; Red: 668 nm center, 14 nm bandwidth; Red Edge: 717 nm center, 12 nm bandwidth; Near-IR: 842 nm center, 57 nm bandwidth. The Ground Sample Distance (GSD) is 8 cm per pixel (per band) at 120 m and it able to capture a 12-bit RAW image (all bands) per second in a field of view of 47.2° HFOV.

3.2 Image Database

The tree canopy image database was obtained with the MicaSense RedEdge-MX camera attached to a drone. The images were captured in the peach orchard located on the Quinta Nova, Tortosendo (Portugal).

For this study, 20 multispectral images of the five channels Red (R), Green (G), Blue (B), Near IR (NIR), and Red Edge (RE) channels were used. In each image, there are approximately 16 tree peach canopy. Therefore, the database includes a total of approximately 320 trees canopy.

The R, G, B, NIR, and RE image channels are (slightly) spatially misaligned due to the physical distance between each sensor/lens set. This phenomenon is known as parallax. To resolve this issue, the camera manufacturer provides an alignment software [11]. This software was used to align the 5 bands of the respective images. Fig. 2 shows the 5 bands of an image used in this work.

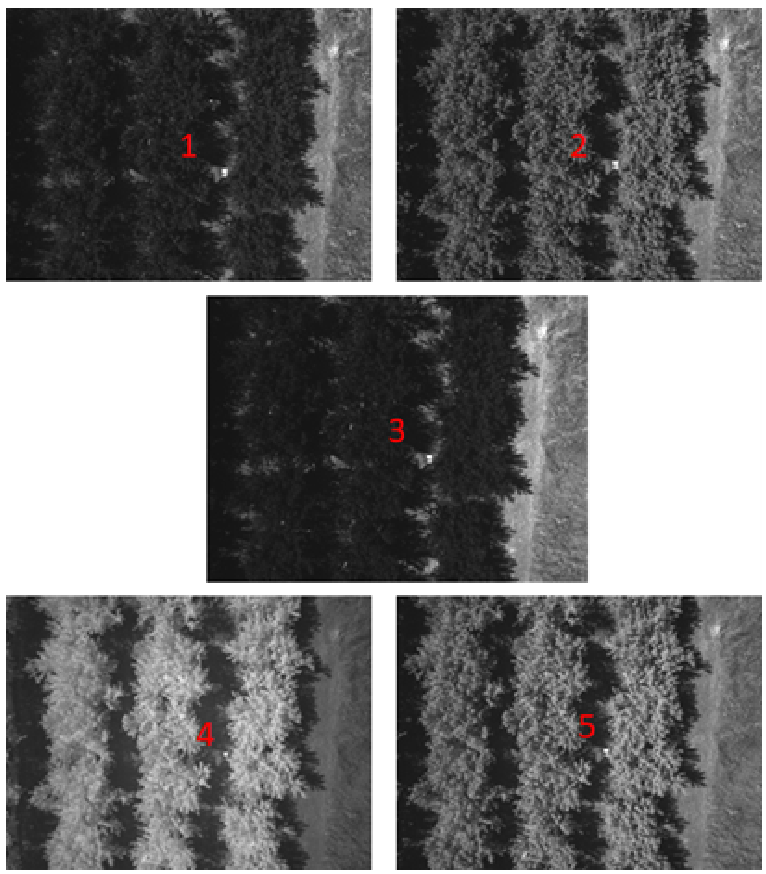

Fig. 2. 1) Channel B, 2) Channel G, 3) Channel R, 4) Channel NIR, 5) Channel RE.

3.3 Vegetation Indexes

Red light is strongly absorbed by the photosynthetic pigments found in green leaves, while near-infrared light crosses or is reflected by living leaf tissues, regardless of their color, acting in the solar reflective spectral range between 390 nm and 1040 nm. Each vegetation index is a number generated by some combination of remote sensor bands (images obtained by the camera) and has some relation to the amount of vegetation (i.e., dense or sparse) in a given image pixel.

Several vegetation indexes are examined and the concept of a formula library is introduced. In this study, a series of equations for different vegetation indexes were used [12]. NDVI is probably the most commonly used index. The difference between the NIR and R reflectance is divided by the sum of the two reflectances, as shown in Equation 1.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{1}$$

NDVI values range from +1.0 to -1.0. Healthy vegetation has low red light reflectance and high near-infrared reflectance, resulting in high NDVI values [13]. At the same time, sparse vegetation such as shrubs and pastures or old plants can give moderate NDVI values (between 0.2 and 0.5) [14]. Thus, increasing positive NDVI values indicate an increase in green vegetation. Conversely, NDVI values near zero and decreasing negative values indicate non-vegetated features, such as barren surfaces (rock and soil), water, snow, ice, and clouds [13] [14].

3.4 Tree Canopy Segmentation

There are several methods of detaining or segmenting objects into digital images, such as the Faster R-CNN method [6] and Mask R-CNN (Mask Region-based Convolutional Neural Network) [15]. These models are just some of the state-of-the-art methods for location and segmentation. In this study, the Faster R-CNN model was used to detect the trees canopy. This model is based on a convolutional neuronal network, which learns how to automatically extract the necessary characteristics of a digital image to solve a computational vision task. The Faster R-CNN network receives a digital image as input and produces the output of the various location positions of the objects found in the input image.

Using machine learning TensorFlow and open source image processing software OpenCV, the proposed model is performed as follows:

– Align the 5-band images (channels) using the Micassense framework.
– Annotation of images: aims to manually locate the objects on which the network is to be trained. For this work, the annotation tool "LabelImg" [16] was used to annotate the tree canopy regions in the training images.
– Training model: the Faster R-CNN model is available in the Github repository Tensorflow Model Garden [17]. We split the annotated tree dataset into training and validation data and performed the training in the model.

3.5 Proposed Method

The proposed method for checking the vitality of a tree is to evaluate the various vegetation indices of a region where a tree canopy is located in a digital image, since these vegetation indices may reflect the health of a tree. For example, healthy vegetation results in high NDVI values and old or not healthy plants result in moderate NDVI values [13] [14].

The pipeline for the proposed method is as follows:

1. Perform canopy segmentation using the Faster R-CNN model. The results are rectangular bounding boxes of the detected tree canopies.
2. Each rectangular region of interest detected by the Faster R-CNN model (step 1) is approximated to an ellipse using the OpenCV library. Since the tree canopies are relatively circular.
3. Calculate the indexes within the ellipse.

4 Results and Discussion

This study shows a method based on convolutional neuronal networks for detection of tree canopies, as well as the application of vegetation indexes as a way to evaluate the vegetation condition of the trees in the peach orchard. Fig. 3 shows the visual result obtained in a test image of the Quinta Nova orchard (Covilhã, Portugal).

The rectangles represent the trees made by the Faster R-CNN model. Ellipses are the regions of interest, obtained from the rectangles found, in which the vegetation indexes corresponding to each tree are obtained.

It can be verified that the model performed detection on all trees. In addition, the detection are well centered in the canopy. Thus, evidence that the model is robust and efficient for the design of trees canopy.

Table 1 shows the results of the NDVI vegetation index analysis for each tree in the test image.

According to Table 1, of the 15 trees in the test image, one (tree 3) had an average NDVI value of 0.88, indicating that this was the tree with the lowest vigor compared to the other trees. Visual analysis of this tree (Figure 3) shows that its branches are sparser. That is, this tree is slightly less dense. This observation justifies its lower average NDVI value compared to the other trees.

It can also be seen that there are two trees (2 and 12) with an average NDVI of 0.95. According to the index, these two trees are the healthiest or developed compared to the others. Most trees (1, 4, 5, 6, 9, 11, and 14) have an average NDVI between 0.93 and 0,94. These trees are also very healthy and with great vigor.

It can also be seen that there are two trees (2 and 12) with an average NDVI of 0.95. According to the index, these two trees are the healthiest and best developed compared to the others. Most trees (1, 4, 5, 6, 9, 11, and 14) have an average NDVI between 0.93 and 0.94. These trees are also very healthy and with great vigor.

Fig. 3. Visual result of the proposed method.

Table 1. Analysis of NDVI vegetation index for the tree canopies in the test image. The green color is the highest value, and the red is the lowest value.

Tree ID	Average	Maximum	Minimum
1	0.94	0.99	0.32
2	0.95	0.99	0.47
3	0.88	0.99	0.25
4	0.94	0.99	0.35
5	0.94	0.99	0.51
6	0.94	0.99	0.34
7	0.90	0.99	0.32
8	0.91	0.98	0.36
9	0.93	0.99	0.26
10	0.92	1.00	0.37
11	0.94	0.99	0.33
12	0.95	1.00	0.44
13	0.91	0.99	0.32
14	0.93	1.00	0.33
15	0.90	0.99	0.32

Table 2 shows the results of four vegetal indexes, whose values are normalized so that a direct comparison between results can be performed. The values of the GNDVI (Green Normalized Difference Vegetation Index), NDRE (Normalized Difference Red Edge Index), REGNDVI (Red Edge Green Normalized Difference Vegetation Index) confirm the analysis previously done with the NDVI index.

Tree 3 is the least developed, as its vegetation index is lower than that of the other trees. Tree 12, on the other hand, is the one with the highest values in most of the indices, so it has the highest vigor in comparison.

Table 2. Average values of five vegetation indexes for the tree canopies in the test image. The green color is the highest value and the red is the lowest value.

Tree ID	NDVI	GNDVI	NDRE	REGNDVI
1	0.94	0.86	0.58	0.57
2	0.95	0.84	0.54	0.57
3	0.88	0.79	0.48	0.51
4	0.94	0.86	0.58	0.56
5	0.94	0.85	0.57	0.57
6	0.94	0.84	0.54	0.57
7	0.90	0.81	0.51	0.52
8	0.91	0.80	0.49	0.53
9	0.93	0.85	0.57	0.54
10	0.92	0.82	0.50	0.55
11	0.94	0.84	0.53	0.57
12	0.95	0.88	0.59	0.56
13	0.91	0.8	0.48	0.52
14	0.93	0.85	0.58	0.56
15	0.90	0.8	0.50	0.52

Fig. 4 shows the training loss curve for the 320 canopy training images and 10000 iterations. Fig. 5 shows the Mean Average Precision (mAP) for validation during training.

Fig. 4. Training loss of canopy detection.

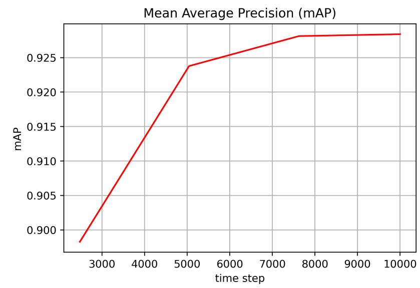

Fig. 5. Mean average precision of validation.

5 Conclusions

The technologies of analysis of multispectral images, captured by drones, manage to be an asset for effective evaluation of vegetation condition of fruit trees. Combining technologies with computational image processing models, makes possible the precise calculation of vegetation indexes, through the use of several bands of combined light, which leads to the prediction of the vigor of the trees. This work has applied a method based on convolutional neural networks for the detection of canopy trees, as well as the application of plant indices as a way to infer the vegetation condition of fruit trees in a peach orchard. The model performed the canopy detection of all trees, which provides a result of its robustness and efficiency. Various vegetation indexes were calculated to infer the vigor of the trees. The values of the GNDVI, NDRE, and REGNDVI indexes confirm the analysis performed with the NDVI index. In the test image, trees are distinguished whose vigor is less, while others have higher than average values. These results allow the fruit grower to analyze in detail and on the ground what are the potential causes of these variations and eventually correct them. Examples like the one used in this work are relevant to support decision-making in agricultural activities, making it possible to optimize resources, reduce time and cost, maximize production, and can be used by farmers, agronomists, and re-searchers. The scope of this study was limited in terms of data (i.e., images) to evaluate non-healthy trees and further study could assess the proposed model with this data.

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