#7465 CASHEW TREES DETECTION AND YIELD ANALYSIS USING UAV-BASED MAP

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ABSTRACT

In this study we developed a novel method to detect cashew trees in an orthophoto map derived from images collected by an unmanned aerial vehicle (UAV). We also suggest a way in which these detections can be used to analyze the yield of the cashew farm. The proposed method uses images analysis to find the tops of trees, to merge different tops located on the same tree, and to segment individual tree. The segmented trees are used in a deep learning framework to know the exact location of cashew trees. The preliminary cashew detection from UAV-based map is promising.

This study can be interesting for developing countries where UAV system are nowadays gaining popularity in agriculture. Given that our method does not require any additional sensor other than the RGB camera onboard the UAV, this low-cost solution is suitable for small and medium cashew farmers. The developed method can also be extended to other types of trees, other than the cashew.

INTRODUCTION

Native to brazil, cashew was brought to Africa due to its qualities of adaptation to difficult soil and climatic conditions. It has therefore been used in several regions of Africa as a species of reforestation since the 1970s. In the 1990s, its world production declined due to the decline in production in India. This situation has led the government of Burkina Faso to emphasize the production of cashew. Engaging more than 45.000 households with 35.000 tones/year, cashew is nowadays one of the most exported horticulture crops in the country (Issa et al. 2017).

One of the big challenges faced by farmers and institutions is to predict the yield with accuracy. The early estimation of the yield is crucial for field management in term of fertilizer and pesticide application in agriculture in general (Geipel et al. 2014), and cashew farming, in particular. An accurate yield estimate is also important for governmental institutions to accurately measure the impact of cashew production and take adequate political decisions.
Several approaches have been introduced for yield prediction of species such as corn, wheat, soybean, etc. These approaches include ground-based field surveys, remote sensing-based methods, or environmental factors techniques (Vuong et al. 2018; Bresilla et al. 2018; Geipel et al. 2014; Wang et al. 2014; Mu et al. 2014; Yang et al. 2019; Maimaitijiang et al. 2020). In Burkina Faso, the yield estimation process is carried out manually and therefore not precise enough.

In this work we show a new approach to identify cashew trees using deep learning model. We also propose a model for estimating the yield.

MATERIALS AND METHODS

Data Collection and Pre-processing

In this study, images have been collected using the DJI Phantom 4 pro v2 drone and the DJI Inspire 1 drone. Both vehicles have a flight time of approximatively 30 minutes. The image size from the camera is 5472x3648 for the Phantom 4 pro v2 drone, and 4000x3000 for the Inspire 1.

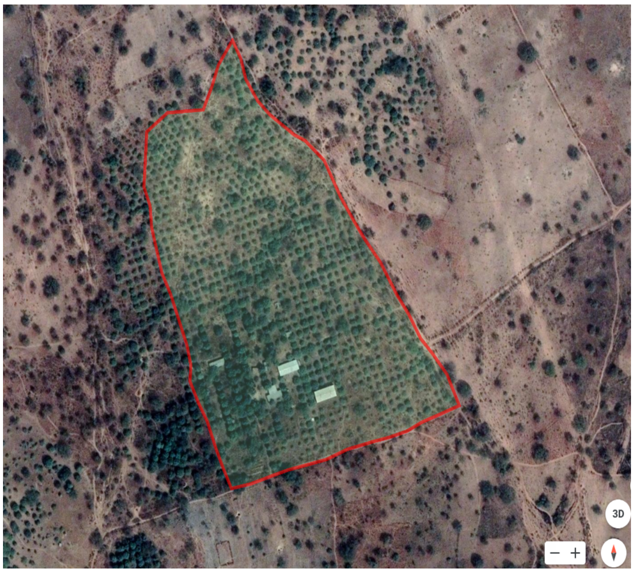

Figure 1. Study area (11°07'35.5"N and 2° 05'52.5"W), image generated using google earth online.

The images have been collected in Léo which is a rural town located in the province of Sissili in Burkina Faso. The study area is marked in Fig. 1. The total mapped area is 11.53 hectares. The images have been collected at the same flight altitude of 36 meters. A total of 1221 images have been collected using four different flight missions.

The collected images are combined in a structure from motion and photogrammetry scheme using the Agisoft Metashape Professional v1.5.5 software (Agisoft 2019). From this process, an orthophoto, a digital surface model (DSM), and digital terrain model (DTM) are produced. The DSM is produced from the point cloud generated from the collected images. It represents the earth surface and everything on it. The DTM is generated by first classifying the point cloud into ground points and non-ground points. Only the ground points are used to generate the DTM which represents the bare-earth surface. All data in this study are generated using the reference frame WGS 84/ UTM zone 30N (EPSG:32630).

Individual Tree Identification

The individual tree identification (ITD) method in this study follows the steps used in the study by (Issouf et al. 2020). Here, we present the most important aspects of the method. For more detail refer to (Issouf et al. 2020; Mohan et al. 2017; Baena et al. 2017). We also present some of the differences adopted in this study.

Using a canopy high model (CHM) computed as the difference between the DSM and the DTM, a local maximum filter is used with fixed window size to find the points which are on the upper surface of each trees. The result of this process is a set of points representing the top part of the trees in the map.

In the study in (Issouf et al. 2020), the trees which were detected are coniferous trees which have conic shape and the maximum filter in this case generally results in a single point representing the top of the tree. In this study, the trees of concern are deciduous trees which have partially a locally flat top surface. Therefore, a maximum filter algorithm will detect several points on the top of the trees. These points, on the same tree, need to be grouped together in order to be effectively used in a subsequent watershed segmentation algorithm to segment out the individual trees. To group several points on the same tree, we use a simple but effective heuristic detailed in the Algorithm 1.

Algorithm 1: Refining local maximum filter result to find tree tops

Input : the set S of detected points x_i, $i = 1, ..., n$
parameter: gap_length, max_distance
Output : set Y of grouped points y_j, $j = 1, ..., m$, $m <= n$

for *each point* x_i **do**
    Find the K-Nearest Neighbours at max_distance from x_i Define a set N and add x_i to the set
    for *each neighbour* **do**
        Generate the line segment between x_i and the neighbour using **Bresenham**'s algorithm;
        Using the CHM, set $g(p)$ the height value of each point on the line segment;
        if *the curve of* $g(p)$ *has a gap (ditch) with size greater of equal to gap_length* **then**
            The neighbour is not associated with x_i
        else
            The point is added to a set N
    if N *is not empty* **then**
        Compute the weighted average of points in N. The weights are the CHM value for each point.;
        Add the computed point to Y;
        Remove all points in N from S
;
return Y. This set represents the tops of the trees on the map

These points representing the tops of the individual trees are used as markers in a marker-controlled watershed segmentation algorithm to segment out individual trees in the map (Myer and Beucher 1990; Meyer 2012). The segmented trees are used in the subsequent detection step to separate the cashew trees from non-cashew trees.

Cashew Tree Detection

To separate the cashew trees from the non-cashew trees in the orthophoto map covering an area of more than 11 hectares, a deep learning detection algorithm is used with the results of the watershed segmentation algorithm. A pure classification algorithm could also be used to simply classify the segmented trees from the orthophoto map. This might however introduce errors because the segmentation results might have several trees segmented as one tree.

The Faster R-CNN with Inception v2 deep neural network architecture is used as done in (Issouf et al. 2020). As explained in this study, using the detection algorithm on the segmented tree images has an advantage over a pure classification. If the segmented tree image contains both the cashew and other tree species the detection algorithm can correctly identify the cashew tree while the classification algorithm might not. Using the individual segmented tree images for detection has an advantage because, there is no need to apply a classification or detection all over the entire orthophoto map. This helps to avoid going through parts of the orthophoto map that obviously do not contain any tree.

The deep learning detection algorithm is implemented, trained, and tested using the python programming language and the TensorFlow object detection API (Huang et al. 2016). A pre-trained model is used to speed up the training and to avoid the problem of overfitting given the limited number of annotated images (Yamashita et al. 2018).

Yield Estimation

For each detected cashew tree, the height and the true area (geographic area) can be respectively estimated from the CHM and the detection process. Using the height and the surface area, we suggest the use of a K-Nearest Neighbors (KNN) algorithm to estimate the yield of a given cashew tree. This is, however, only possible if there is enough ground truth data which can serve as training data. These ground truth data can be collected with farmers from current and historical yield. In this study, these data are not available to validate the KNN algorithm, and therefore the result of the yield estimation is not presented. In addition to the surface area value and the heigh of the cashew tree, other parameters such as the location, the type of soil, the year of production, etc could also be used in the KNN algorithm in order to account for local environmental effect and the time effect in the yield estimation.

RESULTS

In the previous Section, the material and method have been presented. The aerial vehicle platforms used for the data collection have been also presented. The method consists of individual tree identification step which uses a maximum filter analysis and a watershed segmentation algorithm, and a deep learning detection algorithm.

The result of fusing the detected points using the Algorithm 1 is presented. Using the maximum filter analysis several points are detected at the upper surface of each tree. In order to segment the tree as a single tree using the watershed segmentation algorithm, these points are merged so that for each tree only one point is used to represent its top. A sample of the result of the fusion is shown in Fig. 2. Using the merged points as markers in the marker-controlled watershed segmentation, the trees are segmented, and the result is shown in Fig 3. It can be seen that in many cases, individual trees are segmented. However, in some other cases, group of trees are segmented as one tree. This happens because the trees are too closed to each other and have comparative height.

The segmented trees are cropped with a margin from the map and the resulting images are used as input to the deep learning algorithm. Parts of these images (from an area of the overall map) have been used for training the neural network. After the training, the images from another part of the map are used to test the neural network. Fig. 4 shows the detection result. In this figure, the yellow patches represent the original segmented trees from the individual tree identification step. The reddish patches represent the result of the detection of the cashew trees. The deep learning model can effectively detect the cashew trees among other types of trees. Even when the cashew tree belongs to a segmented patch which contains another species of tree, the detection algorithm can still find the cashew tree. This is an advantage over a simple classification technique on the segmented patch.

The detection model is also tested with another dataset which has been collected five months earlier (in May 2020) on a portion of the same site. The result is shown in Fig. 5. It can be seen from this result that the model is able to effectively detect the cashew trees. This result is important because it shows the proposed method is effective on dataset taken at different time and in different conditions.

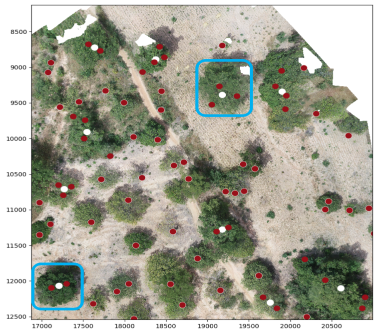

Fig 2: local maximum detection and merging result. The points in the blue rectangles best illustrate the merging result.

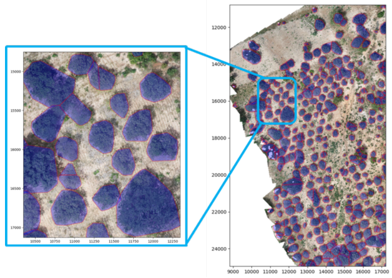

Fig 3: The marker-controlled watershed segmentation result

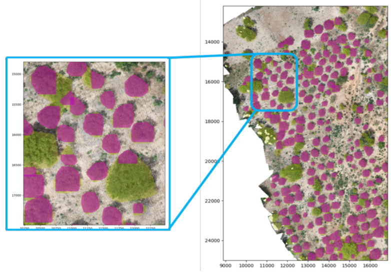

Fig 4: The detection result

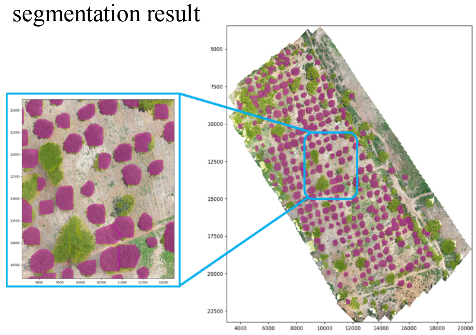

Fig 5: The detection result of cashew trees. Yellow patches represent non-cashew trees, the reddish patches are the detected cashew trees.

CONCLUSIONS AND FUTURE WORK

In this study, a method for detecting cashew trees and estimating the yield have been presented. The process for detecting the cashew trees includes an individual tree identification and a deep learning detection step. The proposed method can effectively detect the cashew trees among other trees. The area of the detected trees can be computed because the orthophoto is georeferenced. This area along with the heigh can be used in a KNN algorithm for yield estimation for each tree.

In the future work, the accuracy of our proposed detection method can be better accessed by using ground truth data. Yield data can also be collected to not only train the KNN algorithm (hyperparameter selection) but also evaluate its performance.

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REFERENCES

Agisoft R. LLC. 2019. St. Petersburg, Agisoft metashape user manual, professional edition, ver. 1.5 [On-line]. https://www.agisoft.com/pdf/metashape-pro_1_5_en.pdf.

Baena S, Moat J, Whaley O, Boyd DS. 2017. Identifying species from the air: UAVs and the very high-resolution challenge for plant conservation, PLOSONE 12(11): 1–21, DOI:10.1371/journal.pone.0188714.

Bresilla K, Perulli GD, Boini A, Morandi B, Grappadelli LC, Manfrini L. 2018. Using Deep Learning - Convolutional Naural Networks (Cnns) For Real-Time Fruit Detection in Trees, 14th International Conference on Precision Agriculture.

Geipel J, Link J, Claupein W. 2014. Combined spectral and spatial modeling of corn yield based on aerial images and crop surface models acquired with an unmanned aircraft system. Remote Sens. 6: 10335–10355.

Huang J, Rathod V, Sun C, Zhu M, Korat-tikara A, Fathi A, Fischer I, Wojna Z, Song Y, Guadarrama S, Murphy K 2016. Speed/accuracy trade-offs for modern convolutional object detectors, CoRR, http://arxiv.org/abs/1611.10012.

Issa W, et al. 2017. Diseases of Cashew Nut Plants (Anacardium Occidentale L.) in Burkina Faso, Advances in Plants and Agriculture Research 6 (February) 7.

Issouf O, Heikki H, Arto V. 2020. Drone based mapping and identification of young spruce stand for semiautonomous cleaning, preprint accepted for IFAC World Congress.

Maimaitijiang M, Sagan V, Sidike P, Hartling, S, Esposito F, Fritsch F. 2020. Soybean yield prediction from UAV using multimodal data fusion and deep learning. Remote Sensing of Environment 237: 1. doi:10.1016/j.rse.2019.111599

Meyer F, Beucher S. 1990. Morphological segmentation, Journal of Visual Communication and Image Representation 1(1): 21–46. https://doi.org/10.1016/1047-3203(90)90014-M.

Meyer F. 2012. The watershed concept and its use in segmentation: A brief history, CoRR, http://arxiv.org/abs/1202.0216.

Mohan M, Silva CA, Klauberg C, Jat P, Catts G, Cardil A, Hudak AT, Dia M. 2017. Individual tree detection from unmanned aerial vehicle (UAV) derived canopy height model in an open canopy mixed conifer forest, Forests, vol. 8, no. 9, 2017, ISSN: 1999-4907. [Online]. https://www.mdpi.com/1999-4907/8/9/340.

Mu H, Zhou L, Dang X, Yuan B. 2019. Winter Wheat Yield Estimation from Multitemporal Remote Sensing Images based on Convolutional Neural Networks, 10th International Workshop on the Analysis of Multitemporal Remote Sensing Images (MultiTemp), Shanghai, China, pp. 1-4, DOI: 10.1109/Multi-Temp.2019.8866918.

Ngo VM, Le-Khac N-A, Kechadi M-T. 2018. An Efficient Data Warehouse for Crop Yield Prediction, 14th International Conference on Precision Agriculture.

Wang L, Tian Y, Yao X, Zhu Y, Cao W. 2014. Predicting grain yield and protein content in wheat by fusing multi-sensor and multi-temporal remote-sensing images. Field Crop Res. 164: 178–188.

Yamashita R, Nishio M, Do R, Togashi K. 2018. Convolutional neural networks: An overview and application in radiology, Insights into Imaging 9: 611 –629.

Yang S, Hu L, Wu H, Fan W, Ren H. 2019. Estimation Model of Winter Wheat Yield Based on UAV Hyperspectral Data, IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium, Yokohama, Japan, pp. 7212-7215, DOI: 10.1109/IGARSS.2019.8898839.