



CISTER

Research Centre in
Real-Time & Embedded
Computing Systems

Technical Report

Deep-Learning-based Automated Palm Tree Counting and Geolocation in Large Farms from Aerial Geotagged Images

Adel Ammar

Anis Koubaa

CISTER-TR-200711

Deep-Learning-based Automated Palm Tree Counting and Geolocation in Large Farms from Aerial Geotagged Images

Adel Ammar, Anis Koubaa

CISTER Research Centre

Polytechnic Institute of Porto (ISEP P.Porto)

Rua Dr. António Bernardino de Almeida, 431

4200-072 Porto

Portugal

Tel.: +351.22.8340509, Fax: +351.22.8321159

E-mail:

<https://www.cister-labs.pt>

Abstract

In this paper, we propose a deep learning framework for the automated counting and geolocation of palm trees from aerial images using convolutional neural networks. For this purpose, we collected aerial images in a palm tree Farm in the Kharj region, in Riyadh Saudi Arabia, using DJI drones, and we built a dataset of around 10,000 instances of palms trees. Then, we developed a convolutional neural network model using the state-of-the-art, Faster R-CNN algorithm. Furthermore, using the geotagged metadata of aerial images, we used photogrammetry concepts and distance corrections to detect the geographical location of detected palms trees automatically. This geolocation technique was tested on two different types of drones (DJI Mavic Pro, and Phantom 4 Pro), and was assessed to provide an average geolocation accuracy of 2.8m. This GPS tagging allows us to uniquely identify palm trees and count their number from a series of drone images, while correctly dealing with the issue of image overlapping. Moreover, it can be generalized to the geolocation of any other objects in UAV images.

Deep-Learning-based Automated Palm Tree Counting and Geolocation in Large Farms from Aerial Geotagged Images

Adel Ammar¹, Anis Koubaa^{1,2}

Abstract—In this paper, we propose a deep learning framework for the automated counting and geolocation of palm trees from aerial images using convolutional neural networks. For this purpose, we collected aerial images in a palm tree Farm in the Kharj region, in Riyadh Saudi Arabia, using DJI drones, and we built a dataset of around 10,000 instances of palms trees. Then, we developed a convolutional neural network model using the state-of-the-art, Faster R-CNN algorithm. Furthermore, using the geotagged metadata of aerial images, we used photogrammetry concepts and distance corrections to detect the geographical location of detected palms trees automatically. This geolocation technique was tested on two different types of drones (DJI Mavic Pro, and Phantom 4 pro), and was assessed to provide an average geolocation accuracy of 2.8m. This GPS tagging allows us to uniquely identify palm trees and count their number from a series of drone images, while correctly dealing with the issue of image overlapping. Moreover, it can be generalized to the geolocation of any other objects in UAV images¹.

Index Terms—Palm Counting, Convolutional Neural Networks, Deep Learning, Faster R-CNN, Unmanned Aerial Vehicles, You Only Look Once (Yolo), Geotagged Images, Palm Geolocation.

I. INTRODUCTION

Tree counting from aerial images is a challenging problem with many applications such as forest inventory, crop estimation, and farm management. Nevertheless, counting the number of palms trees in large farms has been a challenging problem for agriculture authorities due to a massive number of trees and the inefficiency of manual counting approaches. The problem becomes even more laborious and tedious when we also need to identify the GPS location of palm trees for governance purposes. The inefficiency of traditional methods leads to inconsistent data collection about the number of palms, as reported by agriculture experts. For this purpose, we present a deep learning framework for building an inventory of individual palm trees by automatically counting and geolocating them using areal color images collected by unmanned aerial vehicles. The remaining of the paper is organized as follows. Section II discusses the related works that dealt with car detection and aerial image analysis using CNN, and some comparative studies applied to other object detectors. Then, section III describes the datasets and the obtained results.

¹Prince Sultan University, Saudi Arabia.

²CISTER, INESC-TEC, ISEP, Polytechnic Institute of Porto, Portugal.

This work is supported by the Robotics and Internet-of-Things Lab at Prince Sultan University.

¹This is version 1 of the paper

II. RELATED WORKS

There have been several research studies on aerial image processing using deep learning in general, and on palm detection and counting more specifically. Before the area of deep learning, in 2011, Shafri et al. proposed in [1] a detection technique of the oil-palm tree by combining several techniques, namely, edge enhancement, spectral and blob analysis, and segmentation. Reference [2] represents the first work to detect and count palm trees from multispectral QuickBird satellite images using deep learning, dated from 2016. The spatial resolution is 2.4m, but images were processed with the panchromatic band to achieve a 60 cm resolution. The authors developed a convolutional neural network detection with a sliding window approach to localize and classify palm trees in Malaysia with an accuracy of 96%. It was shown that the proposed CNN detector provides better performance as compared to local maximum filter and template matching. In [3], the same authors proposed a classification technique based on AlexNet for the detection of palm trees from high-resolution satellite images. The classification accuracy achieved was 92% to 97% for the study area of palm tree farms of Malaysia. Our work differs from [3] in several aspects. First, we consider high-resolution aerial images rather than satellite images, which provides a higher-resolution of 2 cm/pixel and more apparent features of palm trees. Besides, aerial images provide more up-to-date data as compared to their satellite counterparts. Second, we addressed an object detection problem rather than a classification problem, which requires both the localization and the classification of palm tree instances in images. Third, we do not only detect palm trees, but we also determine its geolocation from geotagged images.

In [4], the objective was to devise a deep learning algorithm for automatically building an inventory of palm trees from aerial images collected by drones. Their contribution was to combine the output of two CNN algorithms where the first is applied to 10 cm/pixel images to learn fine-grain features, and the second neural network 20 cm/pixel to focus on more coarse grain features. The authors achieved detection accuracy values between 91.2 and 98.8% using the orthomosaic of decimeter spatial resolution. Our work differs in several aspects. First, we consider higher-resolution UAV-based aerial images of 2 cm/pixel. We also develop palm detection models based on state-of-the-art algorithms, namely, YoloV3, Faster RCNN, and EfficientDet. Furthermore, we use the metadata of geotagged images to identify the geolocation of detected palms. In our work, we can achieve an accurate

inventory of palm tree farms not only in terms of counting but also for the trees' geolocation.

Some other works considered other types of trees such as [5] that developed a deep learning model for detecting banana trees from aerial images. They have reached the accuracy values of 96.4%, 85.1%, and 75.8% for the altitudes 40, 50, and 60 meters, on the same farm. They have applied deep learning detection algorithm on orthomosaic maps. They have used Faster RCNN with a 42-layered Inception-v2 model feature extractor. Our work improves over [5] in that it can be applied to geotagged images, which enables us to uniquely identify each palm tree by its geolocation, and correctly deal with the issue of overlapping images.

III. EXPERIMENTS



Fig. 1. Sample image of the palm counting and geolocation application.

While the detection of palm infestation is a significant determinant for accurate crop estimation, it needs to be accompanied by a reliable tree counting technique, given the fact that traditional counting methods are inaccurate and inefficient. In order to address this problem, we propose an automated tree counting technique from aerial images, which can also have many other applications such as forest inventory, and farm management. For this aim, we collected a dataset of 217 UAV images taken in a palm tree farm in Kharj region, in Saudi Arabia, with a total of 9,873 instances (8,652 palms, and 1,221 other trees). We manually labeled this dataset using Labelbox [6]. Then, we trained a Faster R-CNN model [7], which is a state-of-the-art two-stage object detection algorithm, on 80% of the dataset (174 images). We obtained a precision of 94% and a recall of 84% for the detection of palm trees, on the testing dataset (43 images). The average precision (AP) at an IoU (Intersection over Union) threshold of 0.5 attains 83%.

Furthermore, we developed an algorithm that tags each detected tree with its GPS location by applying photogrammetry concepts to the metadata extracted from drone images (altitude and GPS location of the drone, image size, calibrated focal length, yaw degree), then applying a distance correction based on the ratio between the drone altitude

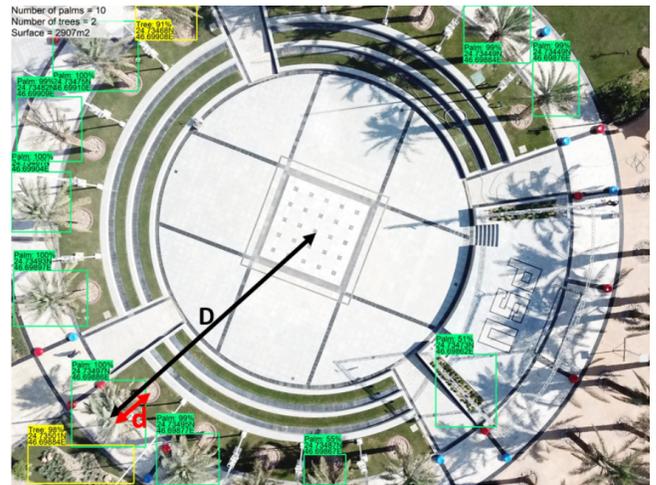
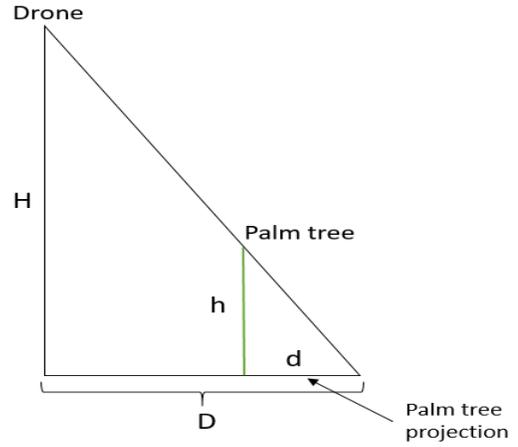


Fig. 2. Distance correction (d) for the geolocation of palm trees from drone images. H is the drone altitude, h is the (average) palm tree height, D is the distance between the image center (drone's vertical projection on earth) and the position of the palm tree summit in the image (supposedly corresponding to the detected bounding box center).

and the estimated average palm height. This geolocation technique was tested on two different types of drones (DJI Mavic Pro, and Phantom 4 pro), and was assessed to provide an average geolocation accuracy of 2.8m, a maximum of 4.9m, and a standard deviation of 1.2m. Figure 1 shows an example of palm detection and geolocation in a UAV image, displaying on top of each detected bounding box the class of each object (palm tree or other tree), the classification confidence level, and the latitude and longitude of the bounding box center.

The GPS tagging allows to uniquely identify, track and count the number of palm trees from a series of drone images, while correctly dealing with the issue of image overlapping while the drone is flying. This procedure can be generalized to the geolocation of any other objects in UAV images.

To geolocate a pixel (x, y) in a drone image, We first calculate the equivalent distance to the central pixel (x_c, y_c)

in the image frame:

$$d_x = \frac{(x - x_c)}{F_c} H$$
$$d_y = \frac{(y_c - y)}{F_c} H$$

Where H is the drone altitude, and F_c is the calibrated focal length of the camera.

Then, we apply a rotation by the value of the flight yaw, to convert (d_x, d_y) to local tangent plane (LTP) coordinates. Finally, we apply a distance correction (Figure 2) based on the average palm tree height to take account of projection issues that induce a difference between the position of the palm tree summit on the image (which corresponds to the center of the detected bounding box) and its footprint.

ACKNOWLEDGMENT

This work is supported by the Robotics and Internet-of-Things Lab of Prince Sultan University.

REFERENCES

- [1] H. Z. M. Shafri, N. Hamdan, and M. I. Saripan, "Semi-automatic detection and counting of oil palm trees from high spatial resolution airborne imagery," *International Journal of Remote Sensing*, vol. 32, no. 8, pp. 2095–2115, 2011.
- [2] W. Li, H. Fu, L. Yu, and A. Cracknell, "Deep learning based oil palm tree detection and counting for high-resolution remote sensing images," *Remote Sensing*, vol. 9, p. 22, 01 2016.
- [3] W. Li, H. Fu, and L. Yu, "Deep convolutional neural network based large-scale oil palm tree detection for high-resolution remote sensing images," in *2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 846–849, July 2017.
- [4] M. Zorteza, M. Nery, B. Ruga, L. B. Carvalho, and A. C. Bastos, "Oil-palm tree detection in aerial images combining deep learning classifiers," in *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*, pp. 657–660, July 2018.
- [5] B. Neupane, T. Horanont, and N. D. Hung, "Deep learning based banana plant detection and counting using high-resolution red-green-blue (rgb) images collected from unmanned aerial vehicle (uav)," *PLOS ONE*, vol. 14, pp. 1–22, 10 2019.
- [6] "Labelbox, [available online at: <https://labelbox.com>], [accessed on 10-02-2020]."
- [7] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with," *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE*, 2017.