UAV-Based Crop Monitoring Through Multispectral Image Processing using Open-Source Tools

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***Abstract*— Aerial imagery map generation depends on the application of several optimization processes for image quality improvement. This is usually done by proprietary software, which removes the possibility of code customization and often requires expensive licenses. This paper proposes the adoption of an open-source aerial mapping tool as a learning platform in the area of unmanned aerial vehicle (UAV) mapping, posing as an alternative to commercial programs in the study of multispectral aerial images applied to crop health monitoring. The paper discusses the results obtained in the experiments using the different processing methods available at the proposed tool.**

***Keywords*— precision agriculture, unmanned aerial vehicles, open-source software, OpenDroneMap**

I. Introduction

Precision agriculture can be described as a management system that divides the fields into zones or blocks, monitors variations in the area, and deals with them using strategies that maximize yields while preserving resources [1]. This monitoring is executed through the assessment of several parameters, for instance, the level of crop photosynthetic activity, commonly acquired via multispectral satellite imagery.

In the last decade, however, the use of unmanned aerial vehicles (UAVs) has arrived as a potential alternative to obtain this information, given its low cost of operation, high flexibility for image acquisition and its spatial and temporal resolution [2]. Nonetheless, to obtain useful insights from these pictures, it is necessary to use mapping software that usually requires expensive licenses.

This paper shows a scenario in which an open-source aerial imaging application called OpenDroneMap (ODM) is implemented to process images obtained by a drone. These pictures are taken during a flight, with the UAV being equipped with a multispectral camera. The result of this procedure is an orthoimage, i.e. a geometrically corrected aerial photograph. The software also applies the calculation of a vegetation health index over the image, enabling crop health monitoring.

II. Vegetation indexes and UAV mapping

The orthoimage allows a better view of the region where the drone performed the flight mission and to produce it, the individual pictures must be submitted to processes such as point cloud production and georeferencing. Once obtained, the image can be further manipulated to display vegetation indexes (VI), allowing the visualization of useful parameters for crop health monitoring, for example, soil nitrogen concentration and plant stress. The following subsections briefly describe some concepts related to these steps.

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A. Normalized Difference Vegetation Index

As stated before, the vegetation indexes offer essential data that are not usually provided by standard observation. The *Normalized Difference Vegetation Index* (NDVI) is the most widely used method to process the obtained images [3]. It relies on wavelengths of visible and near-infrared sunlight reflected by the vegetation to assess the photosynthetic active areas. Also, this index is based on the fact that during photosynthesis, the chlorophyll in leaves absorbs high amounts of visible light, while their cell structures reflect lots of near-infrared light. For a healthy area, this results in more radiation reflected in the near-infrared range rather than in the visible one. The NDVI is obtained using Equation 1 [4]:

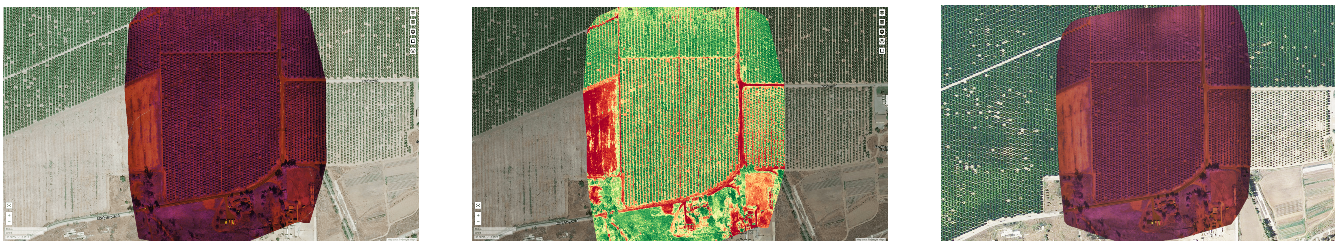
$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{VIS}}{\mathrm{NIR} + \mathrm{VIS}}, \tag{1}$$

where NIR represents the near-infrared (NIR) wavelengths (700–1300 nm) and VIS represents the visible bands (400–700 nm), namely, the red, green, and blue spectrums. This calculation results in a value that ranges from -1 to +1, visually highlighting areas with greater photosynthetic activity.

B. Aerial image processing

Before applying the NDVI, the dataset needs to be assembled into one single orthoimage. However, the pictures acquired during the drone flights present a set of imperfections such as topographic displacements and distortions caused by tilt and by the camera lens, which make them uneligible for producing maps solely by stitching them together. For that, they need to go through several adjustments that may vary according to the approach implemented by the mapping software.

In this work, the process implemented by the adopted open-source tool is the following: first, the dataset is loaded, then the geographic information is extracted and stored in a file. Afterwards, a sparse point cloud is obtained by a process known as Structure from Motion (SfM). This sparse point cloud is densified by undergoing another process called Multi-View Environment (MVE). Finally, the point cloud is transformed into a 3D model and then georeferenced. The orthoimage is obtained by taking a picture of this 3D model, resulting in a GeoTIFF [5], [6].



(a) OpenDroneMap orthoimage. (b) NDVI applied via OpenDroneMap. (c) Pix4D orthoimage.

Fig. 1: Processing results.

III. Simulated Scenario

The proposed scenario simulates the processing of images obtained from a flight over an entire crop field. For that, a dataset was taken from a repository available in an online gallery[1], under permission from the source. This experiment produces an orthoimage by combining 223 aerial photographs, acquired with a MAPIR Survey3W RGN camera that captures the red ($660\,\mathrm{nm}$), green ($550\,\mathrm{nm}$) and NIR ($850\,\mathrm{nm}$) bands.

For the orthoimage generation, the software used was OpenDroneMap, an open-source toolkit for aerial image processing. To explore the possibilities created by this tool, this experiment used a feature called ClusterODM, a functionality that allows the dataset to be split among other ODM instances in the same network, using them as auxiliary processing nodes [7]. The distributed processing scenario is summarized in Figure 2.

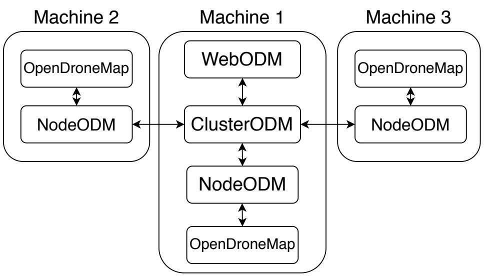


Fig. 2: ClusterODM implementation.

In the experiment, the processing of the dataset is split over three machines. The main unit (machine 1 or M1) uses a graphical interface called WebODM to send the process to ClusterODM, which in turn distributes the images to the other instances, called NodeODM (Machines 2 and 3 or M2 and M3). Once each one finishes processing its own subset, the partial results are merged together into one single orthoimage.

IV. Results

The resulting map is shown in Figure 1a and the NDVI calculated over it by the built-in feature is in Figure 1b. This experiment used three different approaches to visualize the difference in the processing time. This was done by first using only one processing machine and then using the cluster to process with two and three nodes, as depicted in Figure 2. The time each experiment took is displayed in Table I, while the specifications of the machines are in Table II.

TABLE I: Processing time using a different number of nodes.

Processing nodes	M1	M1+M2	M1+M2+M3
Processing time	46m:28s	27m:59s	23m:46s

TABLE II: Processing nodes hardware specification.

	Machine1	Machine2	Machine3
CPU	i7-8700	i5-8400	i5-7500
Memory	16GB DDR4	8GB DDR4	8GB DDR4

The resulting orthoimage produced by the open-source software has a visually acceptable level in comparison with the output produced, for instance, by a proprietary state-of-the-art mapping application such as Pix4D, shown in Figure 1c.

V. Conclusion

This work assesses the applicability of an open and extendable solution for the development of an aerial image mapping and vegetation index calculation platform. Therefore, a set of publicly available pictures were used as input on OpenDroneMap, an open-source drone imagery processing tool, which was able to produce orthoimages without significant visual deformities and obtain vegetation health indicators out-of-the-box via NDVI index calculations. Future works will focus on automating the orthoimage production pipeline and the NDVI calculation for studies in smart farms scenarios.

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