

Towards a Fully Open-Source System for Monitoring of Crops with UAVs in Precision Agriculture

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ABSTRACT

UAVs offer an easy, fast and cost-effective way to acquire data for crop monitoring, alleviating most of the limitations of previously adopted methods. UAVs are frequently used the last years in Precision Agriculture applications as they are considered to be the future of remote sensing, and therefore it is a field that draws a lot of attention. Several software solutions have been developed for processing the images acquired from the UAVs to monitor the crops. However, most of these solutions are offered as commercial products, a fact that increases the already high cost of UAV-based Remote Sensing in Precision Agriculture. In this paper, we propose a fully open source software system that can be used to support the standard workflow required to process the data acquired from the UAVs.

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1 INTRODUCTION

In recent years, Precision Agriculture (PA) has become a very popular research area, that attracts great attention worldwide. Only in the last six years, the total volume of investments in the agricultural sector, focusing on PA technologies, has increased by 80%. Emerging technologies such as Internet of Things (IoT) seem to provide significant potential in Precision Agriculture and Smart Farming (SF) applications [16, 18]. In IoT-based Smart farming, a system is built for monitoring the cultivated fields, targeting in the automation of various important operations such as:

- monitoring of the growth and productivity,
- irrigation process,
- application of fertilizers,
- disease detection,
- weed detection etc.

In this context, these technologies take part in the acquisition of real-time information from the crops. This information can be timely processed and exploited for decision supporting about the management of the crops.

With the ability to monitor large scale cultivated fields in a non destructive way, Remote Sensing (RS) technologies have been widely used in the context of PA and SF. In the past, Remote Sensing was often based on satellite images [2] or images acquired by using manned aircrafts, monitoring crops at several growth stages. However, considering that exploiting manned aircrafts usually results in high costs, and also many times it is not possible to carry out multiple flights to obtain more than a few crop images, this is not always a worthy solution. Regarding satellite imagery, although it has provided a lot of solutions for PA, there are also several downsides:

- the restrictions of the temporal resolutions, as satellites are not always available to capture the necessary images.
- the images acquired often have very low spatial resolution.
- it is often required to wait long periods between acquisition and reception of images.
- the environmental conditions, like clouds, often restrict their reliable use.

In order to overcome these obstacles, Unmanned Aerial Vehicle (UAV) based remote sensing systems have been developed and used in PA applications [17]. UAV-based IoT technology is considered as the future of Remote Sensing in Precision Agriculture [17]. Equipped with sensors of different types, UAVs can be exploited to identify which zones of the crops need different management, and to assist in decision making in various operations. Although a downside in the wider use of UAS in PA is the absence of a standardized workflow for each specific application, a general procedure can be detected [17, 18]. This involves:

- Photogrammetry techniques
- Calculation of the Vegetation Indices (VIs)

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Table 1: Most common software tools used in the literature for image processing

Software tool	Description	Open source
Pix4D	The most commonly used tool. It can be exploited for calculating VIs and/or constructing of 3D models and orthomosaics	✗
QGIS [15]	Usually used for the calculation of the vegetation indices from multispectral data	✓
ArcGis [3]	It can be applied for constructing of 3D models and orthomosaics	✗
Adobe Photoshop [14]	Used in order to correct distortion/use of other image processing methods	✗
Agisoft Photoscan [1]	Used for the construction of 3D models and orthomosaics. Also, it allows the calculation of vegetation indices	✗
MATLAB [7]	Exploited mainly for the calculation of vegetation indices. Also it can be exploited for other image processing methods	✗

- Usually a Geographic Object Based Image Analysis (GEO-BIA)
- Machine Learning (ML) methods

There are a lot of different software solutions for each one of the above steps. The software solutions that are mostly adopted in UAV-based PA applications are summarized in Table 1.

However, most of the software solutions exploited in most cases are commercial, which increases significantly the cost of UAV-based operations in PA, which is one of the major limitations identified on the literature [17]. Given the advantages of Remote Sensing using UAVs in PA, and also the desirability of open source software to decrease the cost, in this paper we present a fully open source framework for performing *all* the operations needed in the generic procedure mentioned above. The workflow of the proposed system is shown in Figure 1. We also give examples on a field of Crocus, in Kozani, Greece. The set of images were acquired as part of the DIAS project for monitoring Crocus fields using UAVs in Kozani.

2 APPLYING PHOTOGRAMMETRIC TECHNIQUES

OpenDroneMap(ODM) is an open-source system, developed in Python programming language. It can be used to perform photogrammetric techniques. ODM produces a variety of photogrammetric products from sparse and dense cloud points to mesh reconstructions and orthomosaics. The software relies on open source libraries such as OpenSfM (an SfM library on top of OpenCV), OpenMVS, and CMVS/PMVS2. It also provides a web interface (WebODM) that includes a map viewer, a 3D viewer, user logins, a plugin system and other features important for drone mapping platforms, making ODM easier to use.

The following steps are automated on WebODM:

- **Image resizing:** Because OpenSfM can efficiently reconstruct a sparse point cloud with low resolution images, the original files can be resized proportionally based on their largest side(Optional).
- **Structure from Motion (SfM):** OpenSfM is a pipeline that ingests sets of images and uses them to reconstructs camera poses and 3D scenes from overlapping coverage of a subject. By default, OpenSfM detects conjugate points in areas

covered by a minimum of three images. This makes sense for images taken by UASs, which usually overlap by 80%. OpenSfM does feature extraction and matching for neighboring images creating depthmaps for each image and then combines them to generate a sparse point cloud of tie points that are refined using bundle adjustment.

- **Dense matching:** This step has the goal of generating a dense point cloud using a Multiple View Stereo (MVS) matching algorithm. The user may choose between two alternatives: OpenMVS (default) or CMVS.
 - OpenMVS: For each input image, the algorithm selects a reference image and creates a stereo pair, following the criterion of a minimal baseline. Afterward, depth-maps are computed for selected pixels in the target image by matching them with the corresponding pixels in the reference image at the lowest possible aggregated cost. Finally, the refined depth-maps are merged together into a single point cloud, avoiding redundancies by applying a neighboring depth maps test.
 - CMVS is an MVS algorithm designed to efficiently generate an accurate dense point cloud. CMVS performs well with a large number of images and few computational resources by decomposing the project into clusters of suitable size. CMVS is more time consuming than OpenSfM.
- **Meshing:** Meshing is essentially the process by which ODM takes the point cloud and creates a network of triangles out of it. The algorithm works to minimize the number of faces used to represent each surface, removing any redundant points along the way.
- **Texturing:** Texturing is the process of adding images to the mesh faces. ODM uses the angles of each face to determine the best image to use for the source pixels.
- **Orthomosaic generation and georeferencing:** Lastly ODM generates an orthomosaic in the PNG format, which is a geometrically corrected image of the entire project area. Furthermore, ODM georeferences both the point cloud and orthomosaic, by using the GPS coordinates that are stored in the Exif metadata of the images. For this final task, ODM relies on

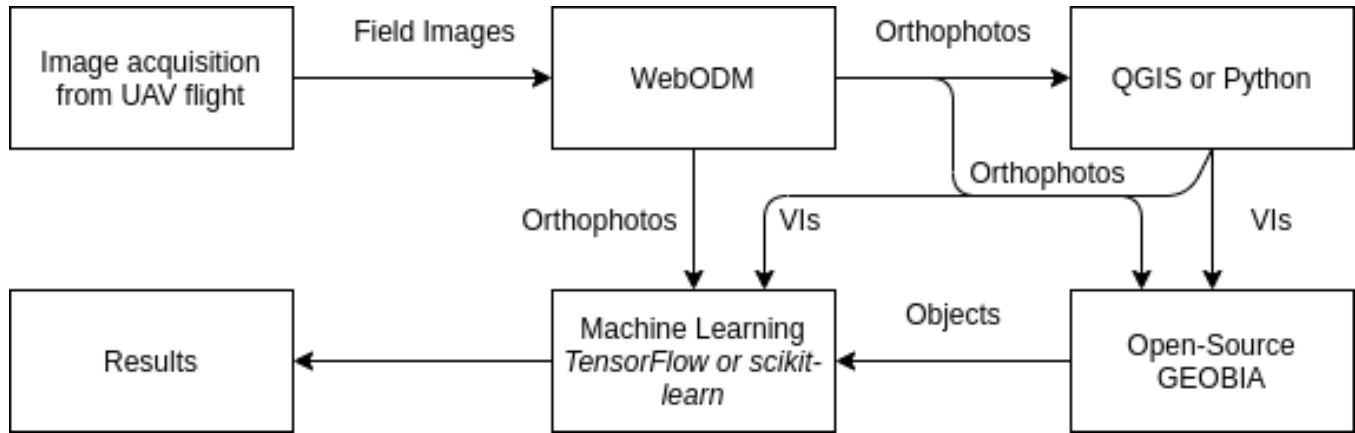


Figure 1: The workflow of the proposed system

both the Geospatial Data Abstraction Library (GDAL) and the Point Data Abstraction Library (PDAL)

The Digital Surface and Terrain Models (DSM and DTM) extracted by using WebODM in the set of images on the Crocus field, are shown in Figure 2. The Orthomosaics generated from the set of images in the NIR and Red bands are shown in Figure 3.

3 CALCULATING VEGETATION INDICES

Having the orthophoto from the previous step, it is easy to calculate the VIs with a number of open-source software solutions. QGIS offers an easy workflow to achieve that by using either the orthophoto in a geotiff format, or the field maps on each band. First, we need to load the image(s) using the "add raster layer" tap, or via drag and drop. Then, we open the raster calculator from QGIS menu and there we write the expression we want to be calculated. The calculation of NDVI using the maps on NIR and RED channels is presented in Figure 3.

Besides using QGIS, there are several more solutions to do this, even by simple using python and apply the simple calculations needed for each VI.

4 OPEN-SOURCE GEOBIA FRAMEWORK

The purpose of GEOBIA is to discriminate objects within agricultural images acquired using UAVs. OBIA groups small pixels together into vector objects, in contrast to most traditional pixel-based image analysis, which processes each pixel separately. Pixel-based classification have become a lot less effective, because of the higher spatial resolution of UAV imagery. That is due to the fact that the relationship between the pixel size and the object size has changed significantly. Therefore object-oriented classification methods are increasing their popularity

In [6], a Python-Based Open Source System for Geographic Object-Based Image Analysis (GEOBIA) is presented. Clewley et al introduce a complete open source framework for performing GEOBIA using a number of open source libraries. All the used libraries are accessed through Python.

The system presented is representing objects as raster clumps and storing the attributes of each object (clump) within a raster

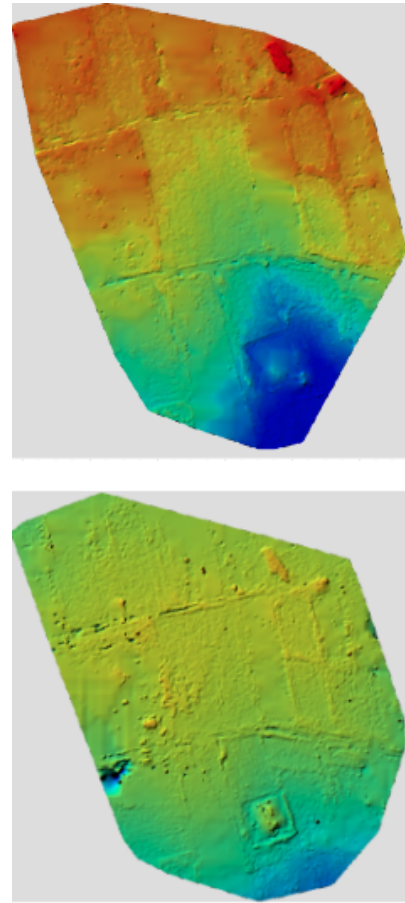


Figure 2: The Digital Surface and Terrain Models of the Crocus field. Generated using WebODM

attribute table (RAT). The following packages are exploited in this system:

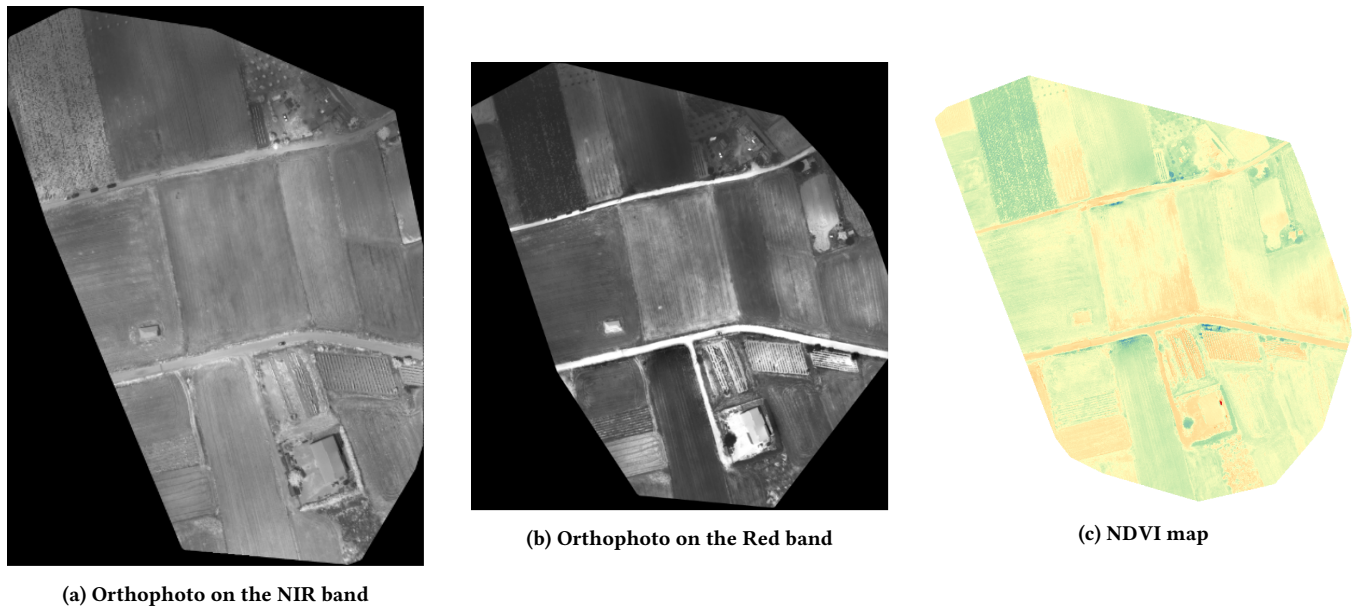


Figure 3: Extracting NDVI map with QGIS

- GDAL; raster data model and input and output (I/O) of common image formats.
- RSGISLib [4]; segmentation and attribution of objects.
- Raster I/O Simplification (RIOS); used to read, write and classify attributed objects.
- KEA Image format [5]; used to store image objects and associated attributes.
- TuiView; used to view data and provides a GUI for rule development.

The segmentation algorithm used is that of Shepherd et al. [12]. Shepherd's algorithm uses an implementation of K-means clustering to generate seeds for the segmentation. The pixels are assigned to the associated cluster center that is closest in colour, by using Euclidean distance. Then, the clumps are iteratively eliminated if they are below the minimum mapping unit threshold. A single Python function is available, within RSGISLib, to perform all of the steps required for the segmentation.

5 EXPLOITING MACHINE LEARNING

Machine Learning (ML) and Data Mining methods are widely used in PA, in order to exploit the information acquired by the UAVs. There is the choice of either the traditional pixel based classification or the object oriented, by applying the GEOBIA workflow first. Machine Learning is widely used in a lot of different domains, and one key factor is the accessibility of a lot of open source ML systems through Python [10].

TensorFlow [13] offers a very useful framework for using Artificial Neural Networks (ANNs), with a lot of different architectures. ANNs are widely used in PA and SF as shown in [8, 9]. Also, scikit-learn [11] offers some useful open source solutions that can be exploited.

6 CONCLUSIONS

In this paper, we proposed a fully open source system for processing images acquired from UAVs to monitor crops in PA applications. This alleviates one of the major limitations for the wider use of UAVs, which is the high cost of the most popular software solutions have been developed. We also show some examples, using a set of images we acquired from a Crocus field in Kozani, Greece.

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