Processamento de imagens adquiridas por VANTs em software opensource.

UAV image processing in open source software

Ana Teodoro

amteodor@fc.up.pt
Dep. Geosciences, Environment and Land Planning, Faculty of Sciences
University of Porto, Porto, Portugal

ABSTRACT

The utilization of Unmanned Aerial Vehicles (UAV) in different remote sensing applications is nowadays generalized. However, these data can result in several software problems related to the huge amount of space requirements for image processing. The traditional supervised classification algorithms cannot solve most of the supervised classification problems. Therefore, Object-Based Image Analysis (OBIA) has been proven to be superior to pixel-based analysis for this type of data. In this work, it was explored the main potentialities of the OBIA method available in the open source software OTB/Monteverdi, in order to generate a land cover map. Ten regions of interest (ROIs), representing the heterogeneity of one scene was considered. First, all the ROIs were segmented and after classified considering a maximum of 4 classes and after a maximum of 6/7 classes. The processing time is always lower for the smaller regions and higher for bigger regions, as expected. The Support Vector Machine (SVM) algorithm seems to be a very good option to lead to this kind of data. However, the poor spectral resolution of the data (only RGB bands are available) is an important factor that limits the performance of the classifiers applied.

Palavras-chave: Segmentação, Classificação, Ocupação do solo

Keywords: Segmentation, Classification, Land Use

INTRODUCTION

Detecting changes is essential for monitoring and disaster response, as well as the map/3D model updating (Wiechert and Gruber, 2010).

An Unmanned Aerial Vehicles (UAV) could be basically defined as an aircraft without a human pilot aboard. Although multi-rotors (Fig. 1 (a)) are probably the most common UAVs used for most of the applications, when the objective is mapping is important to consider a fixed-wing (Fig. 2 (b)). Single-rotor could also be a great solution for some specific applications. Table 1 summarizes the different types of UAVs available and the pros and cons.

Table 1: Different types of UAVs available (http://www.auav.com.au/articles/drone-types/)

	Pros	Cons	Typical Uses
Multi-Rotor	Accessibility Ease of use VTOL and hover flight Good camera control Can operate in a confined area	Short flight times Small payload capacity	Aerial Photography and Video Aerial Inspection
Fixed-Wing	Long endurance Large area coverage Fast flight speed	Launch and recovery needs a lot of space no VTOL/hover Harder to fly, more training needed Expensive	Aerial Mapping, Pipeline and Power line inspection
Single-Rotor	VTOL and hover flight Long endurance (with gas power) Heavier payload capability	More dangerous Harder to fly, more training needed Expensive	Aerial LIDAR laser scanning

VTOL: vertical take-off and landing

UAVs have a lot of advantages in acquiring geographical information: can fly at low altitudes, allowing them to take very high spatial resolution (VHR) images (pixel size of few centimeters) in order to detect small objects/features/events, which has not previously been possible with traditional images (aerial or satellite).

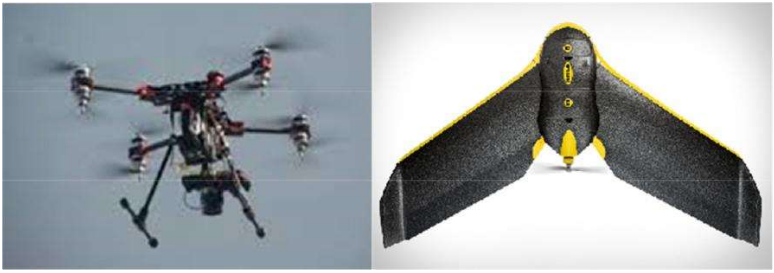


Figure 1: (a) Multi-rotor UAV and (b) Fixed-Wing UAV (SenseFly eBee)

As a small flying vehicle, they are more inexpensive and more flexible than traditional aerial platforms (even more than satellite sensors), and the autonomous capability enables the operator to locate the target area more easily and accurately.

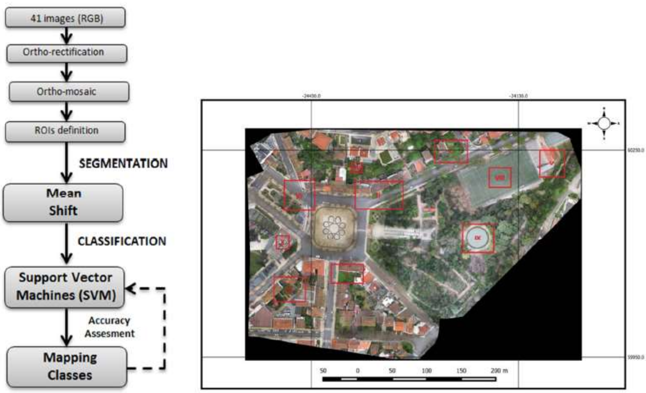
UAVs can supply images even on cloudy days, and the time needed to prepare and initiate the flight is reduced, which allows greater flexibility in scheduling the imagery acquisition. Other advantages of UAVs are their low cost and their great flexibility of configuration, when compared with piloted aircraft, which allows the utilization and testing of low-cost sensors such as conventional digital cameras (Torres-Sánchez, 2014). Due to low payload capabilities of small-and medium-size UAVs, imagery is often acquired with inexpensive off-the-shelf digital cameras.

Most of the image classification algorithms are based on the statistical analysis pixel by pixel. These methods usually present good performance in low spatial and medium spatial resolution images. However, the recent developing of UAV sensors and therefore the advent of very high resolution images (pixel size of a few centimeters) has introduced a new set of possibilities for land-cover. Several studies conclude that Object-Based Images Analysis (OBIA) of small automated extracted features or ones represented in the images by a few grouped pixels presents better results when compared with the traditional pixel-based classification, considering UAV data acquired (Laliberte and Rango, 2009; Pena et al., 2013).

The main objective of this work was to explore the potentialities of the OBIA method available in OTB/Monteverdi open source software version 1.23.0, in order to generate a land-cover map, using UAV data (Teodoro and Araujo, 2016).

METHODOLOGHY

This work describes the results obtained considered the OBIA approach in order to generate a land-cover map, using UAV data. Ten Regions Of Interest (ROIs), representing the heterogeneity of a scene (Coimbra city, Portugal) was considered. The selection of 10 ROIs were also considered in order to solve the problems that come from the image size. These regions were chosen based on areas that could be more problematic and be representative of the scene complexity. The methodology proposed in the present work comprises several steps, as showed in Fig. 2 (a).



a b

Figure 2: (a) Workflow of the methodology employed; (b) Study area (ortho-mosaic) with the 10 ROIs marked

The UAV system used in this work to collect the images was a Swinglet from Sensefly®. The swinglet CAM has a flight time of up to 30 minutes, enabling it to cover up to 6 km^2 in a single flight. Its 12MP RGB camera can shoot aerial imagery at a resolution of down to 4 cm/pixel. These images can then be transformed into ortho-mosaics and 3D elevation models with relative accuracy of down to 3-5 cm. A sequence of 41 overlapped images from Coimbra city was collected in January of 2012. The imagery had a 60% side-lap and a 80% forward-lap. The image ortho-rectification (RMS 0.0076 m in planimetric and 0.742 m in altimetry) and ortho-mosaic computation was performed using Agisoft PhotoScan Professional Edition.

OBIA mainly involves segmentation and classification steps, respectively. Segmentation is the process by which an image is partitioned into a set of spatially contiguous image objects composed of a group of pixels with homogeneity or semantic significance (e.g., Pal and Pal, 1993; Dey et al., 2010). In this work, the Mean Shift Segmentation (MSS) algorithm was used in the segmentation stage and the SVM in the classification procedure. More details about MSS and SVM algorithms could be founded in Huang and Zhang (2008) and Volpi et al., (2013), respectively. This procedure was implemented in OTB/Monteverdi version 1.23.0, which is an open source software.

RESULTS

First, all the ROIs were segmented and after classified, considering a maximum of 4 classes. A random set of objects were generated and classification results are compared with the true information classes in the reference image. Despite the high values of OA obtained for most of the ROIs, considering a maximum of 4 classes, a simple visual analysis allowed to identify several errors, i.e., various objects/elements have been incorrectly classified. In order to improve the classification, more classes (depending of the ROI selected) were defined (Table 2).

Table 2. Classes identified for each ROI in OTB/Monteverdi software considering a maximum of 4 and after a maximum of 7classes

ROI	Classes (maximum of 4)	Classes (maximum of 7)
I	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement 5-Paint 6-Other
II	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement 5-Paint 6-Skylights 7-Other
III	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement 5-Paint 6-Skylights 7-Other
IV	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement 5-Paint 6-Other
V	1-Vegetation 2-Habitation 3-Outdoor benches 4-Bare soil	1-Vegetation 2-Habitation 3-Outdoor benches 4-Bare soil 5-Light rooftop 6-Red pavement
VI	1-Vegetation 2-Habitation 3-Asphalt 4-Pavement	1-Vegetation 2-Habitation 3-Asphault 4-Pavement 5-Paint 6-Other
VII	1-Vegetation 2-Habitation 3-Water 4-Wall	1-Vegetation 2-Habitation 3-Water 4-Wall
VIII	1- Sports flooring 2-White lines 3-Yellow lines	1- Sports flooring 2-White lines 3-Yellow lines
IX	1-Vegetation 2-Water 3-Bare soil	1-Vegetation 2-Water 3-Bare soil
X	1-Rooftop 2-White pipe	1-Rooftop 2-White pipe

In Fig. 3 is presented the classification results for ROIs VII to ROI X considering a maximium of 4 classes

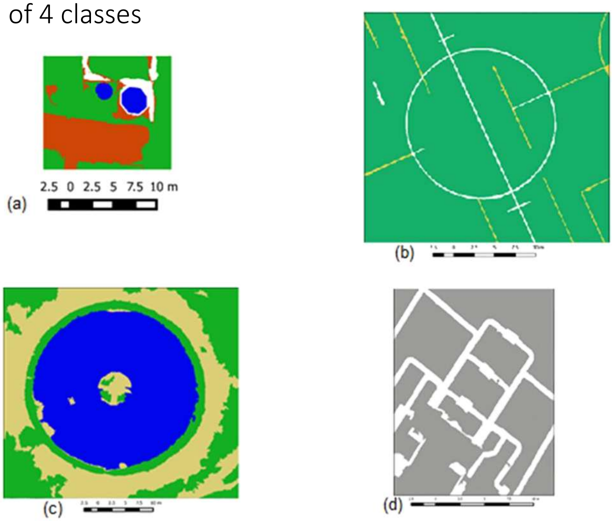


Fig. 3: SVM classification resulted from a MSS segmentation for ROI VII to ROI X, considering a maximum of 4 classes: (a) ROI VII; (b)ROI VIII; (c) ROI IX; (d) ROI X (Teodoro and Araujo, 2016).

DISCUSSION AND CONLUSION

For each ROI, 10 training objects from each class were chosen (when possible). The Overall Accuracy (OA) obtained, considering the classifications performed, are presented in Table 3. The procedure time is identical considering a maximum of 7 classes or a maximum of 4 classes. The processing time is always lower for the smaller regions (e.g. ROI VII) and higher for bigger regions (e.g. ROI III), as expected.

Table 3. OA obtained for each ROI defined considering the OBIA strategy implemented in OTB/Monteverdi software (for a maximum of 4 and 6/7 classes).

ROI	4 classes	6/7 classes
I	90.9%	80.4%
II	90.0%	80.0%
III	93.8%	79.8%
IV	92.7%	84.9%
V	100.0%	91.5%
VI	87.8%	81.1%
VII	96.5%	-
VIII	100.0%	-
IX	95.2%	-
X	100.0%	-

Concluding, the size of UAV scenes is a real problem. In order to consider the amount of data available and produce urban land cover maps, it was necessary select different ROIs with small size and analyzes these regions separately. SVM classifies all of the objects obtained from the segmentation. SVM are less sensitive to overtraining as they are designed specifically to avoid over specifying class decision boundaries. The size of UAV image was also a problem in the accuracy assessment in the OTB/Monteverdi software. The poor spectral resolution of the data (only RGB bands are available) is an important factor that limits the performance of the classifier applied.

ACKNOWLEDGMENTS

The author would like to thank to Sinfic SA (João Marnoto) for ceding the UAV data and to Ricardo Araújo for processing the data.

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