UAV Technology Integration for Remote Sensing Image Analysis

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1 RESEARCH PROBLEM

In this paper, we focus on a multilevel remote sensing framework to integrate information obtained through UAV images, satellite images from Sentinel I and II, radiometric analysis, and spatial information in order to derive informative maps to be used for educated decision support. The goal is the answer to the following questions:

1. Could the classic techniques of remote sensing be used to extract suitable land use maps – suitable in terms of classification accuracy – also for the very high resolution UAV images?
2. Which methods are optimal to analyze UAV images and which benefits could be achieved through the use of more sophisticated techniques, such as the integration of multi-source spatial data to add to the feature vector?
3. Could information from UAV images be merged with data from satellite images in the same area, in order to achieve better results?

2 OUTLINE OF OBJECTIVES

Based on the above research questions, the specific objectives of this project are:

1. To test standard classification methods of remote sensing to UAV multispectral images.
2. To integrate spatial and morphological information of objects to the machine learning methods applied for classification
3. To test advanced classifiers to UAV only and to UAV and satellite data integrated together.

3 STATE OF THE ART

In the last years there was a growing demand for innovative tools to monitor geomorphological aspects for environmental analyses, land use, fragmentation of habitats and risk assessment (Piragnolo et al., 2014a; Piragnolo et al., 2014b; Van Asselen et al., 2013) in particular in rural areas which, in many cases, have proved to be of strategic importance to national and regional economy (Marsden, 2010; van Eupen et al., 2012).

Recently, unmanned aircraft vehicles (UAVs) have seen great attention from the scientific community. There are many aspects regarding this attention, the main one is the prospect to get high-resolution data "on demand" quickly at a relatively low cost. The technology in terms of cost and availability follows the typical development curve: the prices and weight of the components have decreased, data accuracy has increased, and all with a lower power demand, or a constant power and greater durability of the apparatus as a whole. The market has come at a point where the cost for the apparatus, with RGB or multispectral sensors, becomes accessible to amateur users and to a large audience. Research fields are cultural heritage, archaeology, 3D survey, environmental, forestry and precision agriculture (Berni, 2009; Haarbrink and Koers, 2006; Herwitz, 2004; Hunt, 2010; Lelong, 2008; Remondino et al., 2011).

Software for image processing is playing a key role in the diffusion of UAV technology. Since the accuracy of the positioning systems and orientation is not comparable to the classical systems of aerial photogrammetry, software would compensate this limit with a massive use of image matching and structure from motion (SfM) techniques. These techniques, coupled with computer vision algorithms, have led to the development of various software for photogrammetric processing available with commercial licenses and Open Source licenses (Remondino, 2012). Several authors (Grenzdörffer et al., 2008; Sona et al., 2014) have reviewed these new technology and they have reported some problems in photogrammetric, radiometric aspects and data size:

1. Photogrammetric problems concern the limited size and quality of the sensor in the

Piragnolo, M. and Pirotti, F.
UAV Technology Integration for Remote Sensing Image Analysis.
In *Doctoral Consortium (DCGISTAM 2016)*, pages 12-19

camera mounted on the UAV; i.e. missing information regarding the internal orientation, distortion of frames, overlapping of frames, low precision of GPS-INS, high number of ground control point (GCP) required.

2. Radiometric problems are related to image interpretation, correct use of radiometric information, new techniques for the processing of Multispectral Data and calculation of derived index (Honkavaara et al., 2012, Torres-Sanchez et al., 2014).
3. Sensors with high spatial and temporal resolution produce massive data size which increases exponentially (Zaslavsky, 2013). Data size and processing time can be related to the Big Data paradigm: Big Data not only relates to physical storage, but also to the velocity of acquisition and variability of number of files, tables, records and processing time (Singh, 2012).

Photogrammetric techniques will be used to obtain the basic data. The evaluation and improvement of the accuracy of the photogrammetric survey will be studied marginally as it has to be taken into account to provide the spatial error budget. In literature, many authors have proposed new frameworks, GIS environments and objects algorithms in order to solve problems of size and scalability of dataset (Baumann, 2014; Lin et al., 2013; Peña et al., 2013; Zhao and He, 2009). Radiometric analyses for segmentation and classification for GIS environment are the issues that will be considered in this study.

4 METHODOLOGY

The issues that will be considered are related to analysis in GIS environment thus with full spatial support like image interpretation, spectral information, the calculation of derived indices and the integration of other spatial data (data fusion). UAV data will be collected in test areas where ground information is acquired from experts assigning agricultural classes depending on crop type and yield. These data will be analysed in order to understand whether the classic techniques of remote sensing could be applied - i.e. minimum distance, maximum likelihood algorithms (Richards, 2006) and spectral angle mapping SAM (Kruse, 1993) – to correctly return the class of the area. Whether new techniques are necessary and which benefits could be achieved through the use of more advanced techniques, such as the integration of spatial data to increase the number of features describing significantly the phenomena, which we want to model. The integration of information obtained through photogrammetric methods and remote sensing, such as Sentinel-2 data, might improve the quality of derived products such as land use maps. The accuracies of the classification methods will be evaluated by weighing both the feature information from the reflectance from the spectral bands (optical information), and the information on the spatial proximity between classes or morphological information of the objects; spatial and morphological information is the third dimension obtained by photogrammetric technique (Dalponte et al., 2008). A first example of feature vector with elements that will be tested is [b1, b2, b3, b4, b5, H, P] where bx are the bands of wavelength increasing from blue to near infrared, H refers to height from the ground, and P refers to slope. Standard classifiers and sophisticated classifiers such as support vector machines (SVM) (Melgani and Bruzzone, 2004) and Random Forest (Brieman 2001) will be tested.

Considering the continuous use of multiband UAV digital images, it is necessary to structure data and to apply a harmonious management. It is important to manage the "raw" data, and information obtained from the various stages of the processing, to define the standard products; these data must be kept for further analysis.

5 EXPECTED OUTCOME

5.1 Multilevel Remote Sensing Framework

The expected outcome is to set a procedure for classification and relative algorithms for integrating satellite and UAV data with other spatial information. The best algorithms in term of performance could be integrated in a multilevel remote sensing framework. The framework could integrate the information obtained through photogrammetric methods and remote sensing techniques (Figure 1). A first classification at smaller scale will be executed on satellite images. Classification results and accuracies will be evaluated using a control dataset which consists of an independent classification. In case of errors a deeper analysis at larger scale will be necessary, e.g. using aerial or drones orthopotos.

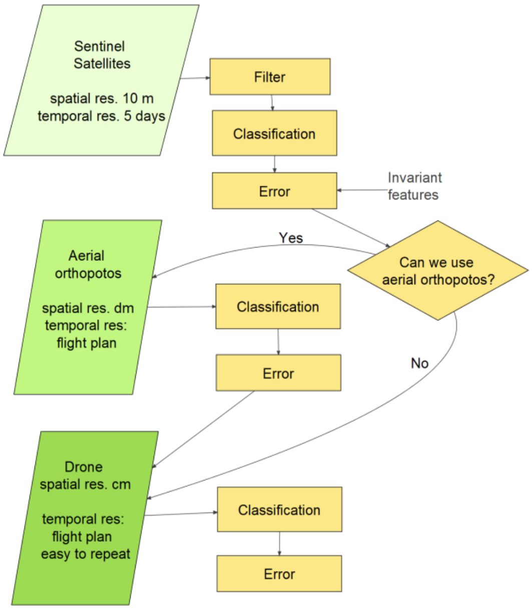

Figure 1: Multilevel framework.

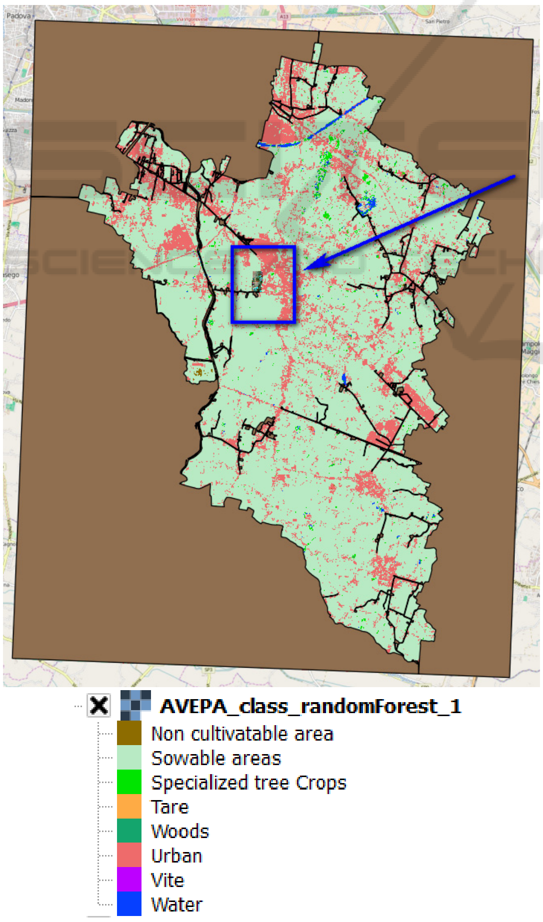

Figure 2: Classification map of land use produced by random forest algorithm.

In Figure 2 we present an initial classification of a test area. It is located at south-east of city of Padova, in Italian Veneto Region. The classification is based on Sentinel II images using random Random Forest algorithm.

Figure 3 shows the UAV image of the test area flown with a drone. The overlap shows a disagreement between Urban class of classification (red pixels) and crops that can be recognized in UAV orthomosaic.

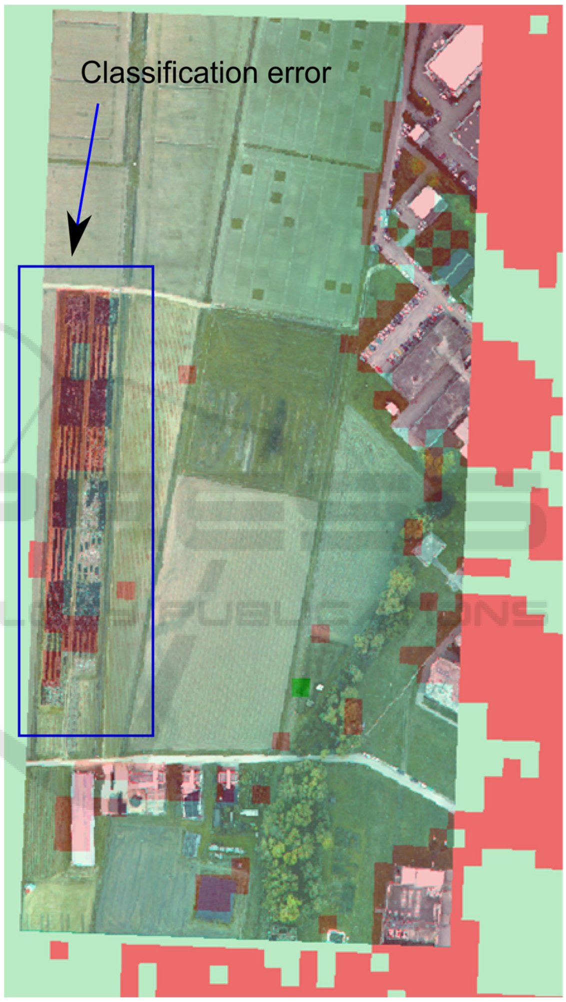

Figure 3: Testing area was flew by drone.

The final classification will be cross validated using a ground-truth dataset acquired by a team of professionals working in the field of land-use maps. The expected outcome is a robust procedure to integrate UAV and satellite data to support decision procedures mainly, but not limited to, the field of agricultural crop administration.

5.2 UAV Fly Test

Testing area is located in Legnaro inside Campus of Agripolis of University of Padova, at south-east of city of Padova, in Italian Veneto Region. It measures 242 meters width, 508 meters height extension, and area is twelve hectares. It was chosen because it contains heterogeneous crops, not flat geomorphology, and ground truth is well known. In November 2015 eighteen ground control points (GCP) were put in the area, and the coordinates were collected with GPS in Real Time Kinematic. The root mean square error of measures is between 0.008 and 0.011 centimetres. Then the area was flown by Agency of Veneto Region for payment in Agriculture (AVEPA), with eBee UAV, Figure 4.

Figure 4: Position of the GCP in the testing area.

Ebee UAV was equipped with three Sensefly cameras, Red Green Blue (RGB), Near Infrared (NIR) and multispectral. RGB camera model was WX. NIR camera model was S110 NIR with three bands, green with central wavelength at 550 nm, red with central wavelength at 625 nm, near infrared with central wavelength at 850 nm. Multispectral camera model was multiSPEC 4C with four bands, green with central wavelength at 550 nm, red with central wavelength at 660 nm, Red edge with central wavelength at 735 nm, near infrared with central wavelength at 790 nm. RGB and NIR camera images had pixel size of 4.5 centimeters. Multispectral camera images had pixel size of 18 centimeters. All images were processed with photogrammetric software Agisoft Photoscan, and then orthorectified. The error calculated by Photoscan is 0.396 pixel (Table 1). Single band orthomosaic were exported as GeoTIFF file.

Table 1: GCP errors calculated with Photoscan.

GCP	XY error (m)	Z error (m)	Error (m)	Proj.	Error (pix)
1	0.0198	0.0002	0.0198	86	0.3340
2	0.0291	-0.0089	0.0304	83	0.3630
3	0.0286	0.0074	0.0295	75	0.3180
4	0.0260	-0.0109	0.0281	92	0.4170
5	0.0156	0.0233	0.0280	106	0.3440
6	0.0331	-0.0307	0.0452	102	0.3180
7	0.0498	-0.0051	0.0500	91	0.4220
8	0.0237	-0.0394	0.0460	109	0.3430
9	0.0193	-0.0069	0.0205	91	0.5160
10	0.0324	0.0783	0.0848	81	0.3980
11	0.0115	-0.0082	0.0141	85	0.4350
12	0.0316	0.0116	0.0336	88	0.3780
13	0.0111	-0.0116	0.0160	116	0.4260
14	0.0480	0.0392	0.0620	84	0.3470
15	0.0267	-0.0550	0.0611	100	0.4100
16	0.0562	0.0613	0.0832	89	0.4590
17	0.0467	-0.0005	0.0467	78	0.3540
18	0.0300	-0.0135	0.0329	45	0.5410
Tot	0.0198	0.0002	0.0456		0.3960

5.3 Classification

In the previous step we have orthorectified nine bands. Then we have selected seven bands in order to have continuous spectrum coverage without overlaps (Table 2), and we uploaded the images in QGis.

Table 2: Bands selected for the classification test.

Band	Camera	Wavelength nm
Blue	RGB	450
Green	multiSPEC 4C	550
Red	NIR	625
Red	multiSPEC 4C	660
Red Edge	multiSPEC 4C	735
Nir	multiSPEC 4C	790
Nir	NIR	850

We used Semi-Automatic Classification Plugin Version 4.9. To test two algorithms, Minimum Distance and Maximum Likelihood, we chose four classes that are, 1 - urban, 2 - ploughed land, 3- crops and 4- vegetation, and we identified regions of interest (ROI) using the specific tool. Minimum Distance classification is shown in Figure 5.

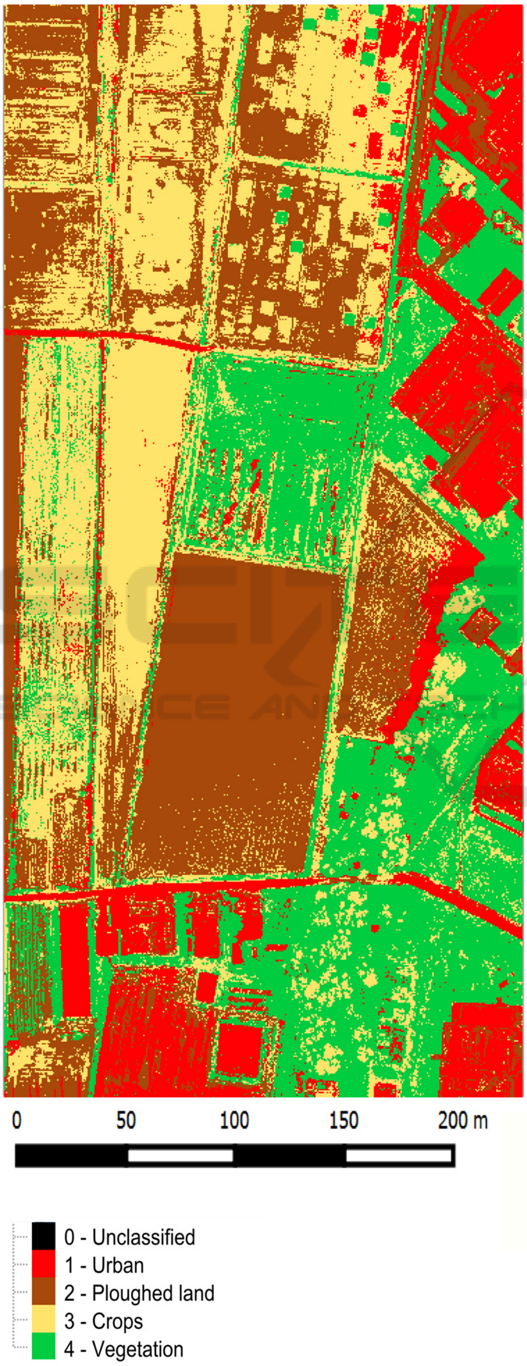

Figure 5: Classification with Minimum Distance algorithm.

In order to asses the classification accuracy a comparison ROI was created and it was used to calculate error matrix (Table 3) and Kappa index. Kappa index for Minimum Distance classfication is 0.64. Then we applied the same procedure for Maximum Likelihood algorithm. Figure 6 shows the classification map, and Table 4 shows error matrix. Kappa index for Maximum likelihood is 0.92.

Figure 6: Classification with Maximum likelihood algorithm.

Table 3: Error matrix for Minimum Distance classification.

	Reference				
Class	1	2	3	4	Tot.
1	32718	4313	0	479	37510
2	10779	389257	2276	0	402312
3	877	53722	32506	29239	116344
4	0	0	6793	50438	57231
Tot.	44374	447292	41575	80156	613397

Table 4: Error matrix for Maximum likelihood classification.

	Reference				
Class	1	2	3	4	Tot.
1	42746	306	0	0	43052
2	1438	442206	6342	0	449986
3	0	4610	27994	842	33446
4	190	170	7239	79314	86913
Tot.	44374	447292	41575	80156	613397

5.4 Conclusion

This work is preliminary analysis to explore the potentiality of Satellite images coupled with UAV images. We have defined a procedure for integrating satellite and UAV data, and we have tested two classic remote sensing algorithms, Minimum distance and Maximum likelihood with UAV data. Images were collected with eBee drone, using with different sensors. Then they were orthorectified and classified in four classes, urban, ploughed land, crops and vegetation. The accuracy of classification was estimated with K index. Maximum Likelihood got 0.91, while Minimum Distance got 0.64. In literature Maximum Likelihood algorithm is one of the most popular classifiers used in remote sensing from satellite. In this preliminary test with images from drone, Maximum Likelihood algorithm gives better result than Minimum Distance classifier. In Figure 7 we can see two comparisons between the algorithms and ground truth. On left images, Minimum Distance algorithm classifies trees as buildings, while Maximum Likelihood assigns trees to vegetation class. On right images Minimum Distance Algorithm produces confused classification. Maximum Likelihood is more precise, but it mixes crops and vegetation.

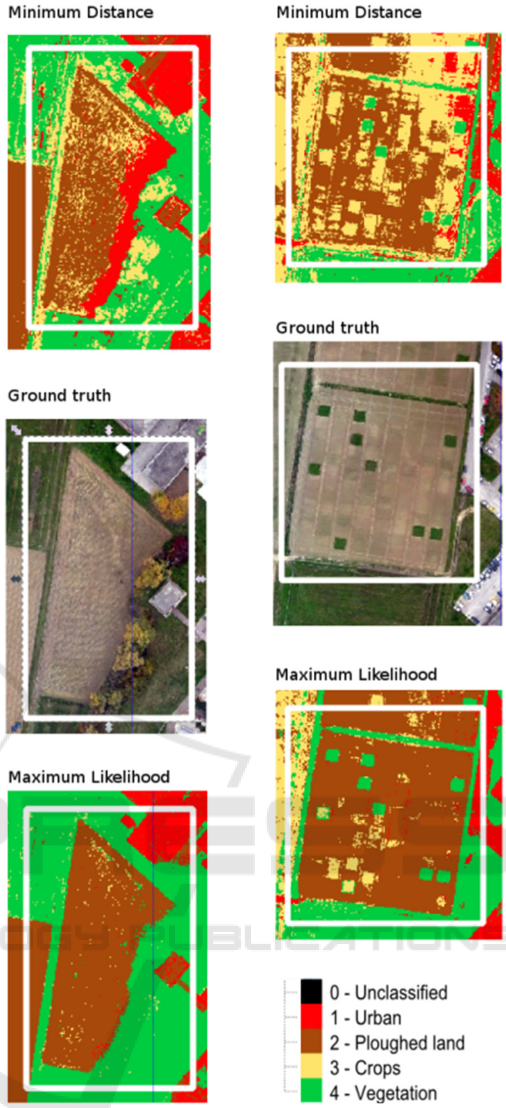

Figure 7: Comparison between classifications obtained two Minimum Distance and Maximum Likelihood algorithms.

6 STAGE OF THE RESEARCH

At the moment the research is at initial phase as the project started a few months ago. In this contribution we want to present the research question and the methods which will be tested in the project.

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