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INCREASING LAND CLASSIFICATION ACCURACY USING UNMANNED AERIAL VEHICLES (UAVs) WITH MULTISPECTRAL LIDAR SENSOR

Gabriel POPESCU, Octavian Laurentiu BALOTA, Daniela IORDAN

University of Agronomic Sciences and Veterinary Medicine of Bucharest, 59 Marasti Blvd, District 1, Bucharest, Romania

Corresponding author email: gabistpop@yahoo.com

Abstract

The paper presents how the use of multispectral LiDAR intensity data for classification has high potentials to increase land classification accuracy. Traditionally, classification of LiDAR data refers to the separation of terrain from other objects based on elevations (range data). Up to about 70% of overall accuracy can be achieved using intensity data only. Land classification accuracy, of about 80%, can be achieved by incorporating both the geometric and radiometric record of LiDAR data. Range and scan/incidence angle have prominent effect on the radiometric correction of intensity data. Radiometric correction of LiDAR intensity data is required for potential use of the LiDAR intensity in land cover classification and radiometric correction can be achieved day or night with similar good results. Current research involves the use of image segmentation and object oriented classification techniques to improve the classification results. The increased number of wavelengths in a sensor has the effect of increasing the information content that can be derived from the target surface and allowing surveying professionals to address many more applications using a single-sensor solution. The complementary information of multispectral LiDAR data may greatly improve the classification performance, especially in the complex urban areas. Use of a minimum of three intensity images from a multi-wavelength laser scanner and 3D information included in the digital surface model (DSM) has the potential for land cover and land use classification. Over 90% of overall accuracy is achieved via using multispectral LiDAR point clouds for 3D land cover classification.

Key words: *LiDAR, photogrammetry, remote sensing, UAVs*

INTRODUCTION

UAV LiDAR involves mounting a laser scanner on an unmanned aerial vehicle (UAV) to measure the height of points in the landscape below the UAV. LiDAR actually means Light Detection And Ranging and an UAV LiDAR System is shown below, in Figure 1.

Figure 1. Unmanned aerial vehicles (UAV) with LiDAR, INS and GNSS

The LiDAR instrument fires rapid pulses of laser light at a surface, some at up to 150,000 pulses per second. Light moves at a constant and known speed so the LiDAR sensors can easily calculate the distance between itself and the target with high accuracy. By repeating this in quick succession the instrument builds up a complex map of the surface it is measuring. LiDAR uses ultraviolet, visible, or near infrared light to image objects. As the sensor is moving, the height, location and orientation of the instrument must be included to determine the position of the laser pulse at the time of sending and the time of return. This extra information is crucial to the data's integrity.

LiDAR scanners can capture hundreds of square kilometres in a single day and by measuring 10-80 points per square meter, a very detailed digital model of a landscape can be created. The accuracy of the measurements allows the 3D models created to be used in any planning, design, and decision making processes across many sectors. LiDAR sensors can also pierce dense canopy and vegetation, making it possible to capture bare earth structure that satellites cannot see, as well as

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ground cover in enough detail to allow vegetation categorization and change monitoring. We will always need a technology to map the bare earth topography accurately and in great detail. Aerial imagery will never provide that information under closed canopies. This means that UAVs with multispectral LiDAR sensor is a very appropriate technology to stay, unless alternative technologies such as interferometric synthetic aperture radar (InSAR) take over laser scanning, which seems improbable in the short term.

Classifying remote sensing imageries to obtain reliable and accurate land cover and land use information depends on many factors such as complexity of landscape, the remote sensing data selected, image processing and classification methods, etc. Land cover is defined as the observed physical cover including the vegetation (natural or planted) and human constructions that cover the earth's surface. Land cover includes water, ice, bare rock, and sand surfaces. Land use, which concerns the purpose or function for which the land is being used, should be considered separately from land cover type.

Remote sensing applications for land cover and land cover change provide high quality multispectral and multitemporal data at the global and regional scales. Frequent mapping by satellite is necessary not only to detect land cover change but to provide land cover products with increasing completeness and accuracies. The in situ data are needed for monitoring of land cover, vegetation migration, and related phenomena, and are also used as ground truth for validation of land cover and land cover change measurements by satellites or other aerial platforms. In situ data will also be necessary to the development of internationally-agreed protocols for land cover and land cover change observations and products. LiDAR uses laser signals in RGB, NIR and thermal IR spectrum for determining ranges between the sensor and objects on the ground and it is used intensively in applications such as generation of DTM/DSM, city modelling and building extraction, environmental modelling, topographic surveying, 3D land cover classification, vegetation mapping, shallow water bathymetry and target recognition. LiDAR sensor records the backscatter energy (intensity data) from objects on the ground and traditionally, classification of LiDAR data referred to the separation of terrain from other objects based on elevations (range data). Nowadays, is under investigation the using intensity data (radiometric correction values) of LiDAR for distinguishing different target materials.

MATERIALS AND METHODS

Several recently studies have indicated that LiDAR and spectral image fusion may improve land cover classification accuracy (Zhou W., 2013). However, most studies focused on multispectral or hyperspectral images and comparisons between LiDAR with different spectral images are sparse. The last studies in 2016 use object-based classification that considers both spatial and spectral features to distinguish different land cover types, improving the accuracy of land cover mapping.

The present paper uses the theoretical and practical experience of the authors in geomatics domain and especially in photogrammetry and lidargrammetry. This review provides an overview of recent research and differential trend to other reviews that has reported UAVs flights experiments on the new multispectral and hyperspectral LiDAR sensors. The paper was inspired by a multispectral scanner named Titan by Optech, shown in Figure 2 (Eric van Rees, 2015).

Figure 2. Optech Titan Multispectral LiDAR System

This type of sensor includes full gyro-stabilization compatibility and a fully-programmable scanner for significantly

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boosting point density with narrower FOVs. Passive imagery support is available via fully-embedded high-resolution metric mapping cameras, including multispectral, thermal, NIR and RGB options.

This latest trend in the development of LiDAR technology considers a different approach to aerial laser scanning point clouds, one that can create land cover maps more effectively than typical topographic methods, providing a tool for high-density topographic surveying which can be useful for land cover and land use classification. Such a data source can even be an alternative or a supplement to photogrammetric data collection. The potential of multispectral airborne laser scanning in land cover mapping was presented in a few publications (Bakula, 2015; Wichmann et al., 2015).

In the Figure 3, it is shown LiDAR wavelength sensitivities for a broad spectrum of application, which is a relationship between wavelengths and reflectance properties of objects.

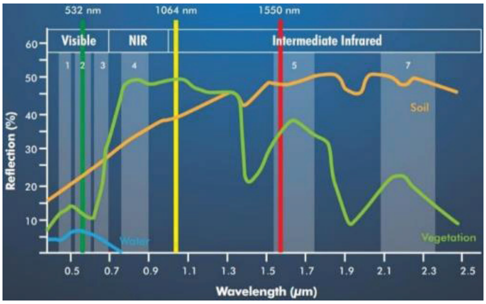

Figure 3. LiDAR wavelength sensitivities (Titan Brochure and Specifications, 2015)

The objective of the paper is to show the success of such experiments, problems that must be solved, use of processing algorithms and results obtained after the flight and data processing for increasing land classification accuracy using UAVs with multispectral LiDAR sensor.

RESULTS AND DISCUSSIONS

Unmanned Aerial Vehicles (UAVs) equiped with multispectral LiDAR sensor provide a new opportunity for aerial close distance data collection. It provides high density topographic surveying and is also a useful tool for land cover mapping. Use of a minimum of three intensity images from a multiwavelength laser scanner and 3D information included in the digital surface model has the potential for land cover and land use classification. The sensor must includes full gyro-stabilization compatibility, which aids in providing predictable point distribution, as well as a fully-programmable scanner, which provides point density increases at narrower FOVs. For example, Optech's Titan presented by Dr. Paul LaRocque from Optech's VP of Advanced Technology, is not focused strictly on active imaging, so, the sensor accommodates passive imagery using fully embedded high-resolution metric mapping cameras such as multispectral RGB, NIR and thermal IR. Full-waveform recording for each wavelength is available for use when necessary.

For remotely sensed data and imagery (panchromatic, color infrared, multispectral, hyperspectral, lidar, radar), it is necessary to account for positional accuracy, blurring properties, registration errors, and spatiotemporal resolution to properly integrate the data into a model-based analysis. In addition, data products derived from these sources (e.g., land cover classification) will have their own uncertainties that may need to be accounted for in subsequent analyses.

Accuracy and precision in spatial analysis depend on the data used to build the model and the amount of missing data. Accuracy and precision are a function of the data and what is being estimated or predicted. In physical process models, accuracy refers how closely the simulation matches the average behavior of the observed system, whereas precision is a measure of the variance (National Academies of Sciences, Engineering, and Medicine, 2016).

Land cover classification can be done in two ways: either *a priori* or *a posteriori*.

In an *a priori* classification system, the classes are abstract conceptualizations of the types actually occurring. The approach is based upon definition of classes before any data collection actually takes place. Thus all possible combinations of diagnostic criteria must be dealt with beforehand in the classification. For example for plant taxonomy and soil science, in the field each sample plot is identified and labelled according to the classification adopted.

The main advantage is that classes are standardized independent of the area and the means used. The disadvantage is that this method is rigid, as some of the field samples may not be easily assignable to one of the pre-defined classes.

A posteriori classification differs fundamentally by its direct approach and its freedom from preconceived notions. The approach is based upon definition of classes after clustering the field samples collected. An example is the Braun-Blanquet method, used in vegetation science (Di Gregorio A., Jansen L.J.M., 2005).

A posteriori approach implies a minimum of generalization. This type of classification better fits the collected field observations in a specific area. At the same time, however, because an *a posteriori* classification depends on the specific area described and is adapted to local conditions, it is unable to define standardized classes. Clustering of samples to define the classes can only be done after data collection and the relevance of certain criteria in a certain area may be limited when used elsewhere.

We consider that a combination of LiDAR and different spectral images (multispectral or hyperspectral images) has many advantages. The integration of hyperspectral images and LiDAR has higher accuracy than hyperspectral only and LiDAR only. Most accuracy indices for hyperspectral images are higher than those for multispectral images. So, based on the previous researches since 2016 (Tee-Ann Teo and Chun-Hsuan Huang, 2016), it is proposed below, in Figure 4, a scheme for integration spatial LiDAR features and spectral features to identify different land cover types, subsequently improving the accuracy of land cover mapping. The main steps in the proposed scheme include spatial and spectral feature extractions, image segmentation and classification. The integration of different spectral data with LiDAR data is based on using the same mapping coordinates for LiDAR and spectral orthoimages, which provide 3D shape information and color information to separate different objects, respectively. The combinations include:

a) LiDAR integrated with traditional 4-band (blue, green, red, infrared) multispectral images;

b) LiDAR integrated with advanced 8-band (coastal, blue, green, yellow, red, red edge, NIR 1, NIR 2) multispectral images;

c) LiDAR integrated with hyper-spectral images.

Although the multispectral and hyperspectral image wavelengths overlap between 400 nm - 1050 nm, the band width of a hyperspectral image is only 10 nm, smaller than that of a multispectral image. Therefore, the classification capability of hyperspectral imagery is better than that of multispectral imagery and we can quantify the difference between multispectral and hyperspectral images in LiDAR assisted classification.

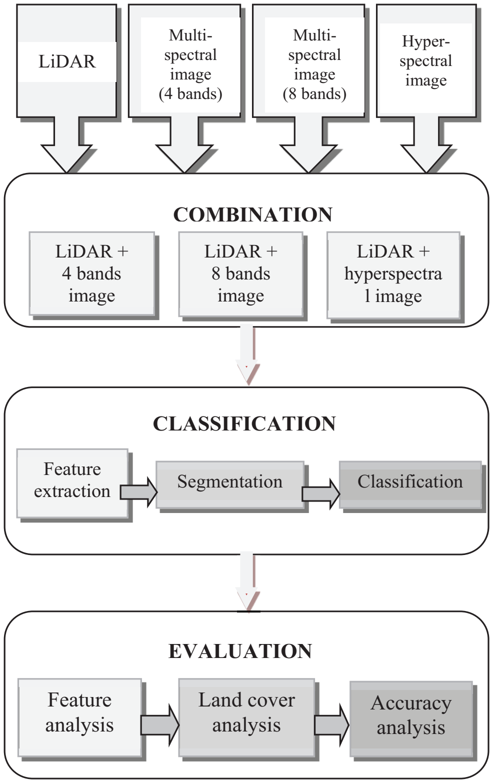

Figure 4. The proposed scheme

The aim of segmentation is to merge pixels with similar attributes into a region. We used rasterized LiDAR and spectral orthoimages as the input layers for segmentation and combined elevation attributes from LiDAR data and radiometric attributes from orthoimages in the segmentation. The segmentation considers both attribute and shape factors. Pixels with similar height and spectral attributes are merged into a region. The attribute is the pixel value of the input layer whereas the shape factor is the shape of the segmented object. The segment concept is based on the heterogeneity index, expressed in equation 1. The heterogeneity combines the attribute (expressed in equation 2) and shape (expressed in equation 3) factors. The segmentation is a bottom up method that starts from a pixel. Each pixel is treated as a small object and neighbourhood pixels are added to calculate the heterogeneity index. If the heterogeneity index meets the predefined criterion, these pixels are merged together (Tee-Ann Teo and Chun-Hsuan Huang, 2016).

$$h = w_{attribute} * h_{attribute} + w_{shape} * h_{shape} \quad (1)$$

$$h_{attribute} = \Sigma\, w_i\, \sigma_i\,, \; unde\ i=1 \ldots n \quad (2)$$

$$h_{shape} = w_{smoothness} * h_{smoothness} + + w_{compactness} * h_{compactness} \quad (3)$$

$$h_{smoothness} = l/b$$

$$h_{compactness} = l/\sqrt{n}$$

where:

h is heterogeneity index;

$h_{attribute}$ and h_{shape} are attribute and shape indices;

$w_{attribute}$ and w_{shape} are weights;

$w_{attribute} + w_{shape} = 1$;

w_i is weight for layer i;

σ_i is the standard deviation of layer i;

$h_{smoothness}$ and $h_{compactness}$ are smoothness and compactness indices, respectively, for shape;

l is perimeter; b is smaller length of size;

and n is area.

In general, the advantages of this method are that the different layers have different weights and the segmentation considers the attribute (pixel value) and also the shape of objects.

After segmentation, an object-based classification rather than pixel-based classification is performed. Each separated region after segmentation is a candidate object for classification. An object-based classification considering the characteristics of elevation, spectral, texture, roughness, and shape information is performed to separate different land cover types. The object based image analysis approach is an effective way to classify the multispectral LiDAR point clouds data for 3D land cover classification. The definition of classification indexes is very attractive for the separation of different height vegetation and spectral similar objects point clouds. Repeating the segmentation with different scale parameters make the boundaries of 3D land cover types distinguish from other objects features easily. For evaluating the classification results, confusion matrix and error statistics for nine classes must be calculated, and overall accuracy obtained should be over 91% (Zou Xiaoliang et al., 2016).

Multispectral LiDAR point clouds are segmented and classified on the basis of return signal intensity images from more than three channels raw data. The intensity depends on the reflectance of the ground material and laser pulse wavelength. Numbers of all returns point clouds, and elevation information from maximum first returns and minimum last returns are main factors for classification. Meanwhile, different objects reflective characteristic in three channels are taken into account for classification. Water is best penetrated in green spectrum, and a slightly reflective in NIR and IR spectrum. Power line is strongly reflective in NIR and IR spectrum and slightly reflective in green spectrum. Vegetation is strongly reflective in NIR spectrum, and slightly reflective in visible green spectrum. Soil is best reflective in intermediate IR and vegetation can be easily distinguished from soil and water.

After the image objects classification of multispectral point clouds, is performed the accuracy assessment by comparing randomly distributed sampled points in reference imagery with the classification results. The reference points are compared with classification results at the same locations. We use these known reference points to assess the validity of the classification results, to calculate a confusion matrix, to derive the user's accuracy and producer's accuracy for each class, to calculate errors of commission and omission for each class, and to compute an overall accuracy and kappa statistics for the classification results.

The accuracy of the image based point cloud can be evaluated using precisely measured ground reference points. So, the dense matching can provide points with RGB information for every pixel of the image and the identification of corresponding reference points is possible. Based on the coordinate residuals, both horizontal and vertical accuracies can be calculated.

Direct comparison with ground reference points (in the case of LiDAR point clouds) is nearly impossible due to lower point cloud density, as ground targets may be difficult to find based on LiDAR intensity information and point coordinates and, in addition, sparse data can introduces additional error. Since the LiDAR point clouds are usually used for surface modeling, the vertical accuracy was estimated on the basis of the created Digital Surface Model (DSM). After removing noise points, the DSM of the grid size equal 0.1 m are interpolated and compared against heights of ground reference points. Then the vertical RMSE is calculated based on height residuals.

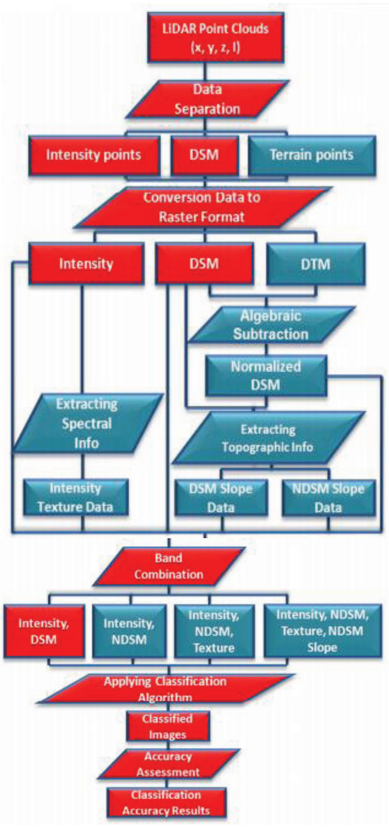

Figure 5. Image Classification Workflow
(Dr. Paul LaRocque, Optech Inc., 2014)

In the Figure 5, it is shown the workflow of image classification described by Optech Inc. in 2014.

Radiometric correction of LiDAR intensity data is required for potential use of the LiDAR intensity in land cover classification. Radiometric correction can be achieved day and night with consistent results. Range and scan/incidence angle have prominent effect on the radiometric correction of intensity data.

The use of multispectral LiDAR intensity data for classification has high potentials. Up to about 70% of overall accuracy can be achieved using intensity data only, and classification accuracy of about 80% can be achieved by incorporating both the geometric and radiometric record of LiDAR data. Some current research involves the use of image segmentation and object oriented classification techniques to improve the classification results (Shaker A. et al., 2015).

The fusion of multi-wavelength laser intensity images and elevation data, with the additional use of textural information derived from granulometric analysis of images, help to improve the accuracy of classification significantly (overall accuracy of classification of over 90%).

CONCLUSIONS

If we look in the history of airborne LiDAR, we can see that innovation is constant. We have begun from putting a laser on an aeroplane, to LiDAR profiling of forests, scanning LiDARs, full waveform LiDARs, etc. We are now seeing expansion towards multispectral LiDAR and prototypes of hyperspectral LiDAR are also being developed. These use white laser light generated using a supercontinuum principle. Like RADAR, LiDAR can also be made polarimetric, which would certainly help in vegetation mapping. Moreover, we are also seeing photon-counting or Geiger-mode airborne LiDAR including the promise of high point densities from 9 km flying height. On another front, oblique multi-view aerial photography is emerging, thus increasing our capacity to extract 3D information about forest canopies.

LiDAR is becoming more and more spectrally oriented with developments such as multispectral LiDAR and imagery is moving towards better 3D extraction capabilities using multi-view oblique imagery. For these reasons, we think that both, multispectral LiDAR and imagery, will have a dense matching thriving side by side for the next decade.

Multispectral LiDAR is a very recent development that may help with vegetation classification. For example, tree species information is not only necessary for timber inventory but also for habitat studies and other analysis. While LiDAR has been extremely useful for mapping forest structure, its use for species identification is still marginal. Although 3D data contains information for distinguishing species to some extent, a lot of discriminating power comes from the analysis of spectral signatures of color imagery. Tree foliage color in the visible and infrared band indeed differs between certain species. However, the radiometric corrections necessary to attenuate the variation in the sun-object-sensor geometry in airborne images are very complex. Multispectral LiDAR provides a way to measure multichannel intensities with a constant geometry, which make them easier to correct.

Multispectral LiDAR system is a new promising research domain, especially in applications of 3D land cover classification, seamless shallow water bathymetry, forest inventory and vegetative classification, disaster response and topographic mapping. Further research is needed to combine multispectral LiDAR point clouds with other ancillary data such as digital surface model (DSM) and imagery in order to improve the associated precision. For example, multispectral imaging sensors on agricultural drones will allow the farmer manage crops and soil more effectively. This multispectral imaging agriculture remote sensing technology use Green, Red, Red-Edge and NIR wavebands to capture both visible and invisible images of crops and vegetation. LiDAR, multispectral and photogrammetry imagery will be all very closely related technologies. In some sectors and situations, images from all 3 are required to give a full analysis of the terrain, vegetation or structure.

Both land cover spectral information and 3D surface information can be obtained efficiently via remote sensing technologies applied to UAVs at close range domain. Spectral images provide spectral features whereas LiDAR point clouds contain 3D spatial features. Therefore, the multisensory data can be integrated to obtain useful information for different applications. This study integrates LiDAR with different spectral features for land cover classification. Because different spectral images have different characteristics, is better to use hyperspectral images or multispectral images, to distinguish different land covers. The main works include features selection, object-based classification, and evaluation. In features selection appropriate features must be selected according to the land cover characteristics. Object-based classification must be implemented using image segmentation and supervised classification. Finally, different combinations must be evaluated, using reference data to provide comprehensive analyses.

We can conclude with the following three considerations, demonstrated practically by Tee-Ann Teo and Chun-Hsuan Huang in 2016:

a) The integration of hyperspectral images and LiDAR has higher accuracy than hyperspectral only and LiDAR only. The improvement rate reached 6% for the data fusion approach. The combination of spatial and spectral data is beneficial for land cover identification;
b) For the comparison of traditional 4-band and advanced 8-band multispectral images in data fusion the improvement rate of 8-band images reached 9% for 12 classes. The additional coastal, yellow, red edge, and NIR2 are useful for land cover mapping. The additional bands lead to improvement in the classification accuracies for areca, crop, and bare ground ;
c) LiDAR features are useful for separating man-made objects and vegetation, whereas spectral features are useful for separating different vegetation types. In the 8-band multispectral images comparison with hyperspectral images, using narrow hyperspectral bands has better accuracy than broad spectral bands in species classification. The improvement rate of hyperspectral images reached 13% for 12 classes.

Custom land cover measurement products will continue to be important in satisfying the needs of the wide range of land cover data users, and the development of an integrated set of land cover measurements, that encompasses individual mission-specific land cover products, will be necessary to address the many gaps and inconsistencies that hinder comprehensive data analysis and forecasting.

Validation should be an inherent part of every land cover research effort for satellite data. While satellite data must be verified by *in situ* measurements, the multispectral LiDAR data captured with UAVs, from an altitude of 50-100 m, are themselves *in situ* data for others satellite data. Probability-based sampling design provides accuracy measurements that allow the user to understand the magnitude of error. In the future, we believe that the use of UAVs will extend globally to non-urban areas. The ground control points currently used for improving geolocation mapping will be a network of sensors spread over fields and collaborating with remote sensing tasks. While today the processing of data acquired by the UAV is usually performed offline, in the future online data processing and intercommunication functionality will provide aerial works with the ability to further extend from current mapping and modelling applications to more intelligent application activities.

The use of multiple laser diodes in one sensor may be potentially beneficial in refinement of the UAV's attitude and this approach needs further algorithmic developments. In the same time, it is necessary to test in the future research new technologies and algorithms for increasing accuracies for direct and indirect geo-referencing of the multispectral / hyperspectral LiDAR and image point clouds obtained by UAVs equipped with GNSS/IMU/Sensors (Popescu G. et al., 2015).

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