

Extraction of urban parameters from 3D Point-Cloud within GRASS

C.Rebelo⁽¹⁾, A. I Rodrigues⁽¹⁾, B. Neves⁽¹⁾, J. António Tenedório⁽¹⁾, J. Alberto Gonçalves⁽²⁾

⁽¹⁾ e-GEO Research Centre for Geography and Regional Planning, Faculdade de Ciências Sociais e Humanas FCSH, Universidade Nova de Lisboa, Avenida de Berna 26-C, P 1069-061, Lisboa, crebelo@fcsb.unl.pt, brunomaneves@fcsb.unl.pt, amrodrigues@fcsb.unl.pt,

⁽²⁾ Faculdade de Ciências, Universidade do Porto, jagoncal@fc.up.pt

ABSTRACT

Nowadays, efficient technologies like airborne systems with active or passive sensors, required robust and optimized geoprocessing models to acquire geographical information of urban areas, such as the urban parameters associated to buildings. The multiple stereo matching processing of aerial images captured by Unmanned Airborne Systems (UAS) enables the acquisition of dense georeferenced 3D point-cloud. This technology has revealed a great potential for a variety of applications. However, it lacks the evaluation in extraction of urban parameters that involved a third dimension. This work addresses the use of UAS 3D point-cloud in a small urban area of the Lisbon region for the extraction of urban parameter - building façade height. The development of one methodology to the extraction and evaluation of building facade height parameter was performed using free and open source software. Two important tasks were performed: i) the creation of a geoprocessing model within graphical modeler of GRASS 6.4.2. GIS (Geographic Information Systems) to the extraction of UAS points that will define the building façade height; and ii) statistical evaluation of this urban parameter in R software. The use of specific filtering algorithms implemented on GRASS LiDAR library were very useful in the processing of UAS point cloud data for the extraction of urban parameter building façade height.

Key words: UAS, Building Façade Height, Urban Parameter, Evaluation, Buildings

INTRODUCTION

The use of new technologies for the acquisition of 3D geographical data is important for urban planning. One of its most important applications is the evaluation and monitoring of urban parameters and indicators of an urban plan, involving 3D data. The quantification of some urban parameters, such as the buildings' mass and buildings' height, is useful in monitoring the density of built-up areas and on the identification of illegal changes in buildings' height. On the other hand, urban and solar potential analysis are also two important applications that require 3D geographical information, specifically 3D building models.

The multi-source 3D point clouds can be an efficient solution for these urban planning applications, because its usage encourages the development of automated methodologies and the updating of a geographical database on time. New airborne systems for the acquisition of 3D point-cloud have been developed in the last decade, such as Airborne Laser System (also called LiDAR Detection and Ranging system) and more recently the Unmanned Aerial Systems (UAS) imagery. These two systems are very different in the way of acquiring the 3D point-cloud. The LiDAR system is an active remote sensing that acquires directly a point-cloud by millions of pulses, while the UAS is a passive system that acquires stereo aerial images. To generate the UAS point cloud the stereo aerial images pairs must be post-processed by dense image matching techniques, allowing the identification for each point of this cloud the coordinates xyz and RGB values. More information about the technology UAS can be seen in [1].

The first challenge of this study is the evaluation of UAS point cloud in estimation of urban parameter building façade height. The same evaluation had already be made for the LiDAR data of a small urban area located in the south of Portugal, but implemented in proprietary software [2]. In this study the vertical error on building façade height was less than 10 centimeters for 73% of the values estimated.

The next challenge is the use of the GRASS GIS for filtering the UAS point cloud with higher density, about 10 points/m², by using modules that were developed for the LiDAR data. Various authors [3], [4] and [5] have tested the processing of LiDAR point cloud in GRASS GIS, with these modules.

Thus, the objective of this paper is to evaluate the extraction of this urban parameter using UAS point cloud and 3D reference data acquired by traditional photogrammetry, through algorithms implemented in open source GRASS GIS and R.

STUDY AREA AND DATASET

The use of 3D point cloud from UAS for the extraction of the urban parameter of height façade was performed in a selected urban area of Amadora, a city located about 10km from Lisbon. The selected geographic area has a total area of 90 hectares, with a width of 150m north to south and 600 m long east to west (Figure 1). The dwelling area is limited in the south by the railway line and in the north by a slum area, with 89 buildings grouped into 7 blocks. The majority of the buildings have five or six floors, with the tiled roofs. Also, there are some scattered trees among the building blocks.



Figure 1: Study area of city Amadora, Portugal.

At the end of last summer this area was covered by 45 stereo aerial images (3000 by 4000 pixels) acquired from a UAS senseFLY at 300 m flight altitude. These stereo aerial images have a higher overlapping between each other, which is about 90% along flight and 60% cross flight overlap. Next, these stereo aerial images with a Ground Sampling Distance (GSD) of 4 centimeters were processed by multiple stereo matching to generate the 3D point cloud data used in this work (Figure 2).

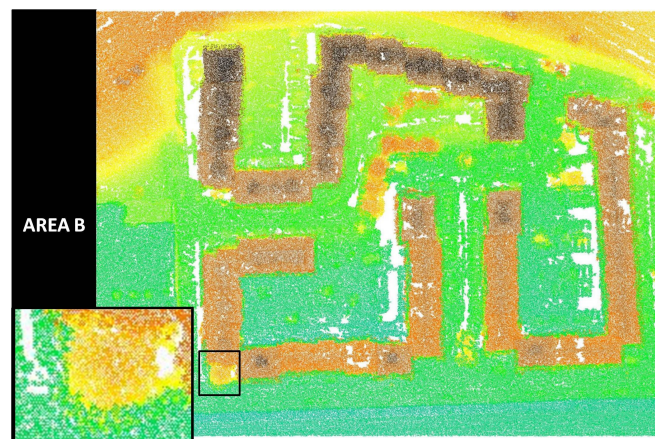


Figure 2: Point cloud data of Area B

The 3D point cloud UAS has a little more above one million of points (1066171 points) with an irregular distribution. The mean density of this point cloud is 11 points per square meter (This means that the distance between points is less than fifty centimeters). The manipulation and processing of the whole point cloud is more difficult, thus the point cloud was split into three areas A, B and C (Figure 1), according to the urban morphology of the buildings. The description of the point cloud data of each area can be seen in table 1. Latter it will become clear why the urban morphology of these areas is important in the estimation of this urban parameter.

Table 1. *Characterization of point-cloud areas*

Area	Area (ha)	Buildings	Number Points	Point density (points/m ²)	Mean distance between points
A	34.4	14	364811	10.6	0.31
B	34.4	43	406185	11.8	0.29
C	24.5	32	295175	10.0	0.32

The point density per square meter is the ratio between the total number points and total area. Although, the mean distance between two closest UAS points is the inverse of the square root of the point density. These parameters will be important in the processing of point cloud to detecting the object's edges.

The large-scale 2D/3D vector data (1:2000) was also important in the development of the methodology presented in next section. These vector data was used as reference in extraction and evaluation of building façade height performed, such as the 3D vector points on the top of roof building and building base elevation to calculate the building façade height reference. Also, the orthomosaic was used for visual inspection, to visualize the results obtained along the methodology.

METHODOLOGY FOR EVALUATION OF BUILDING FAÇADE HEIGHT

The methodology developed included a set of operations which have been implemented in a geoprocessing model. The geoprocessing model was performed through a graphical modeler in the open source software GRASS GIS. The *R* was also used to compute an average building façade height value and for the evaluation of results.

The methodology implemented to estimate an “average building façade height value” for each building from the UAS point cloud is performed in three parts: 1) extraction of a “set of UAS points” that defines the elevation of the top of the building's façade; 2) extraction of a “set of UAS points” near the building base; and 3) the estimation of building's façade height by the trimmed mean of the elevation values of each of the previous points. The flowchart of this methodology is shown in figure 3.

The 3D point data of large scale mapping should be used as reference data along the first and second parts of the methodology. Before the workflow (Figure 3), the UAS point cloud was imported as ASCII file to GRASS vector format. Next this information was partitioned in three areas (Figure 1) within GRASS, to optimize the processing time of these data along the workflow.

The first part is the extraction of a set of UAS points on the top of the building's façade or near the edge of roof. The following steps are need to be followed at this stage: *i*) the extraction of the buildings edge points by the function *v.lidar.edgedetection* of GRASS LiDAR module; and then *ii*) selecting the building's edge points which are within *X* distance (less than one meter) of the reference point located on the edge of roof.

The extraction of a set points that defines the building base elevation was performed in these steps: *i*) the generation of Digital Terrain Model (DTM) using the following functions *v.lidar.growing* and *v.lidar.correction*; and *ii*) selecting UAS points

from DTM which are within X distance (less than one meter) of the reference point located on the sidewalk or near the building's base. The distance X in these two parts should be chosen with reference to the point density.

The last part of the methodology is the computation of the building's façade height based on the difference between the trimmed mean values computed for the elevation points of the top of building façade (trim=0.4) and building base elevation (trim=0.2). The trimmed mean lies between the mean value and median value. This statistic is very useful for excluding outliers for dense point data with a high gradient of elevation values.

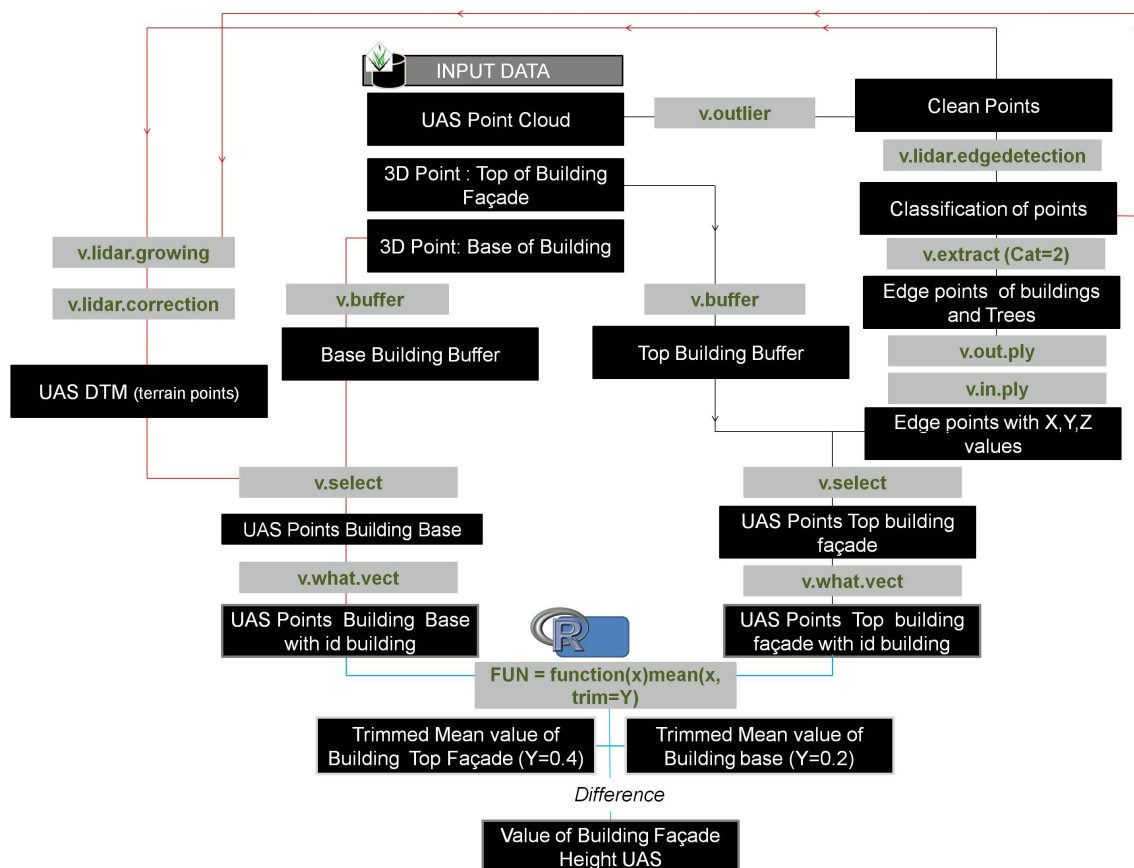


Figure 3. Flowchart for the extraction of building façade height. The red line in the workflow process corresponds to the second part of the methodology and blue line the third part of process.

The evaluation of the results achieved for each building in the urban parameter building façade height was based on the computation of vertical position errors. The vertical error of the building façade height estimated corresponds to the difference between the value estimated from UAS point data and the reference value of 3D vector data. In the next section we can see the magnitude of vertical errors estimated for the 62 buildings of the study area.

The GRASS 6.4.2 algorithms [6] used to filtering the UAS point cloud were important in the results obtained in this work. The function *v.lidaredgedetection* [7], [8], identifies the edges of buildings, trees and streetlamps along the road from a

point cloud (Figure 4). The interpolated height values of each point will be classified by a category attribute value (cat=1, terrain; cat=2, edge; cat=3, uncertain). This classification is useful in the selection of points of interest. In this algorithm the values of the two parameters of interpolation *spline step* in the east (*see*) and north (*sen*) direction have been chosen 3 up to 4 times of planimetric resolution of point cloud [4].

The selection of UAS points near the building's base was made from the Digital Terrain Model (DTM). The DTM was created by the three sequential functions of GRASS LiDAR module (*edge detection*, *growing and correction*).

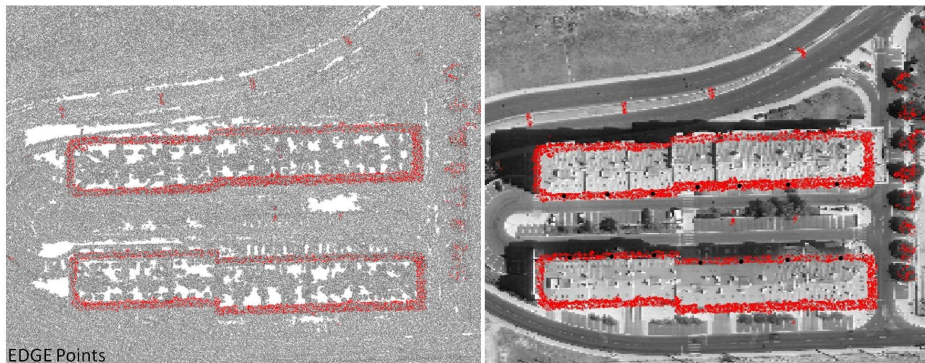


Figure 4. The classification of edge and terrain points of area A. The red points are the edge points and the gray points are the terrain points. In the second image is possible to distinguish the overlapping of these points in orthoimage and the 3D points on the edge of roof building (black circle).

RESULTS

The estimation of the urban parameter building façade height is strongly dependent of the quality of UAS points selected in the end of geoprocessing model (Figure 3). The most error points in DTM are objects located near the building façade, such as trees, streetlamps and cars originate the majority of error points. On the other hand, the error points in edges of buildings are generally identified as balconies or other elements of the façade. These error points affect the estimated value of building façade height.

Thus the edge detection algorithm and DTM process should be made with the best parameters values to minimize these error points. The effect of different spline steps values (~ 0.2 to $2x$ and ~ 0.4 to $4x$) in edge detection for the same area, can be seen in figure 5. The curve of estimated values of building façade does not approximate the true values.

Urban Morphology vs. estimated value of Building Façade Height

In figure 5 is possible to visualize the behaviour of the edge detection algorithm for different urban morphologies in areas A, B and C.

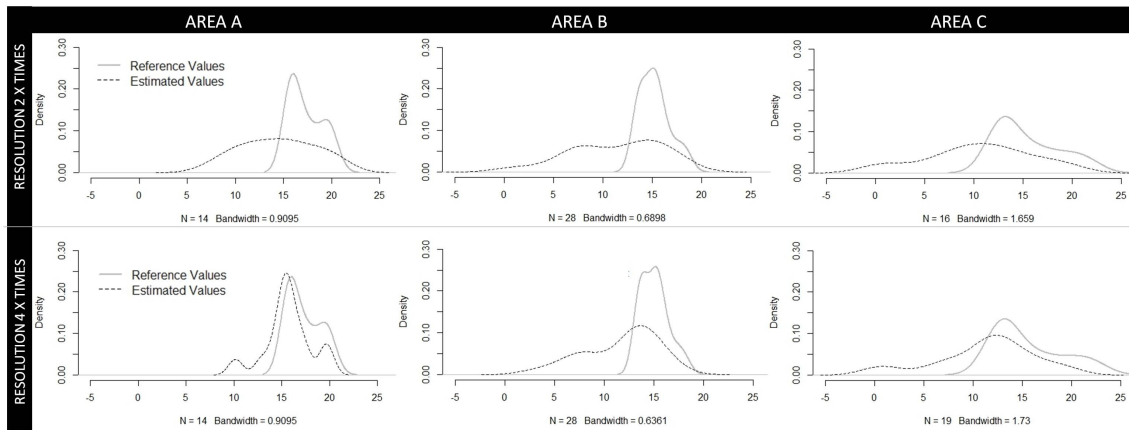


Figure 5. Empirical density functions (reference building height façade vs. estimated buildings façade for each area) for two different spline steps of the edge detection.

Empirical density functions for area A with highest resolution (4x the planimetric resolution of point cloud) show the best results (the estimated curve approximates the true values). This is because area A (Figure 5) is very homogeneous and with regular buildings. The worst results are recorded for the heights estimated in area B and C. In fact, these areas have a more complex urban morphology, irregular in the case of area B and regular buildings blocks in area C. There is strong evidence (Figure 5) that the estimation of urban parameter building façade height from UAS depends on urban morphology.

Vertical Error

The evaluation of the results achieved for each building in the urban parameter building façade height was based on vertical error. The vertical error of the building façade height estimated corresponds to the difference between the building façade height value estimated from UAS point cloud and the reference value from 3D vector data.

The magnitude of vertical errors in the estimation of building façade height from UAS point cloud can be seen in figures 6 and 7. About 30% of the total buildings were not estimated (Figure 6, black buildings), due to the following: i) the presence of data gaps near the buildings (Figure 2), due to shadows; and ii) the presence of points errors in DTM or edge detection. The urban parameter building façade height was estimated for 62 buildings (Figure 6, the remaining ones), of which about 45% of these have an error under one meter.



Figure 6. *Distribution of vertical error for each area and by the edge detection process (different spline step values).*

Moreover the distribution of vertical errors along the true height of building façade (between 12 and 21 meters) for the 62 buildings, can be seen in figure 7. The most residual values are less than two meters. The residual values of area B present a strong variability.

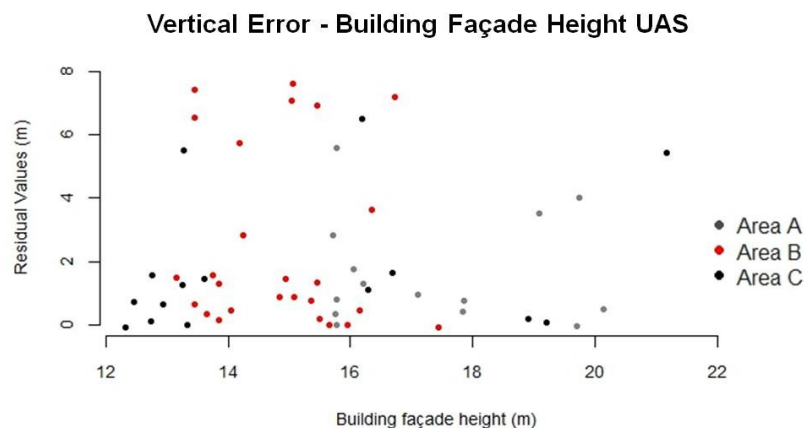


Figure 7. *Distribution of vertical errors along the different areas A, B and C.*

DISCUSSION

This work introduced a method to evaluate the urban parameter of building façade height estimated from a 3D point cloud acquired by ultra-light UAS's imagery using free and open-source.

The most useful characteristics of the open source software GRASS GIS for this study are:

- the capacity to recognize the dense point cloud with about 9 million of points (original data) and to create various tiles of the original data;

- more suitable and more efficient in the manipulation of these type of data (with higher density) when compared with proprietary software GIS;

- the new module of format ply was very important to record the coordinates of each point in attribute table. Using the old way the processing time to do this crucial operation would have been about half day for each area.

- and the edge detection algorithm used was very useful for the selecting of building points of the top.

In the methodology developed for this work the use of module LiDAR GRASS was very useful in edge detection of buildings and in extraction of points near buildings that are classified as terrain in DTM. However, it is important to mention that the growing algorithm, used to define the building inside, does not offer expected results with the UAS 3D point cloud data, because the algorithm needs information of first and last pulse LiDAR.

We believe that the UAS technology for acquisition of 3D point cloud at "low cost" can be very useful in urban planning. The performance of the 3D point cloud data in this study demonstrated that there is a strong correlation between the urban morphology and the accuracy of height value of the building façade. To evaluate and understand this result more investigation is necessary, concerning the nature of these 3D point cloud (where the tilt of images can be very higher than the reference value of 5°) and performance in recording and processing 3D point values. On the other hand, in the future the methodology employed here should be tested in GRASS 7.0.

However, new developments in open source software are needed to support the analysis and manipulation of dense 3D cloud points acquired by UAS or other technology. In order to increase the performance of UAS point-cloud processing the development of new algorithms which make possible the use of RGB and Infrared values on filtering of data is necessary.

REFERENCES

- [1] KUNG, O.; STRECHA, C.; BEYELER, A.; ZUFFEREY, J.C.; FLOREANO D.; FUA, P.; AND GERVAIX F. (2011), "The accuracy of automatic photogrammetric techniques on ultra-light UAV imagery." *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXVIII, pp.1–6.
- [2] REBELO, C.; GONÇALVES, J.A.; TENEDÓRIO, J.A. (2012), "Análise de dados LiDAR para a extracção de parâmetros urbanísticos". *Actas do Congresso Ibérico de Geografia*. Santiago de Compostela, 24-27 Outubro, pp. 940-951.
- [3] BARAZZETTI, L.; BROVELLI, M.A. (2008), "LiDAR filtering: testing of an automatic procedure developed in the free open source GIS GRASS." *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. Vol. XXXVII. Part B4. Beijing, pp.359-366.
- [4] BROVELLI, M.A.; CANNATA, M.; LONGONI, U.M. (2002), "Managing and processing LIDAR data within GRASS." *Proceedings of the Open source GIS-GRASS users conference*, Trento, Italy.
- [5] SÁNCHEZ, R.A.; BROVELLI M.A. (2007), "LiDAR data filtering with GRASS GIS for the determination of digital terrain models." *I Jornadas de SIG Libre*. Universitat de Girona.

[6] NETELER, M; MITASOVA H. (2008), "OPEN SOURCE GIS. A GRASS GIS Approach." The International Series in Engineering and Computer Science: Vol 773. 3rd. Springer. New York. 406 pp.

[7] LiDAR GRASS Wiki, <http://grasswiki.osgeo.org/wiki/LIDAR>

[8] GRASS website: <http://grass.itc.it/>

ACKNOWLEDGEMENTS

This paper presents research results of the Strategic Project of e-GEO (PEst-OE/SADG/UI0161/2011) Research Centre for Geography and Regional Planning funded by the Portuguese State Budget through the Fundação para a Ciência e a Tecnologia. The dataset was kindly provided by SINFIC, S.A. The authors would like to thank João Marnoto of the SINFIC Company for providing all the information and their helpful comments.