HIERARCHICAL OBJECT-BASED CLASSIFICATION OF DENSE URBAN AREAS BY INTEGRATING HIGH SPATIAL RESOLUTION SATELLITE IMAGES AND LIDAR ELEVATION DATA

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ABSTRACT:

In Portugal, updating municipal plans (1:10 000) is required every ten years. High spatial resolution imagery has shown its potential for detailed urban land cover mapping at large scales. However, shadows are a major problem in those images and especially in the case of urban environments. The purpose of this study is to develop a less time consuming and less expensive alternative approach to the traditional geographic data extraction for municipal plans production. A hierarchical object oriented classification method, that combines a multitemporal data set of high resolution satellite imagery and Light Detection And Ranging (LiDAR) data, is presented for the Municipality of Lisbon. A histogram thresholding method and a Spectral Shape Index (SSI) are initially applied to discriminate shadowed from non-shadowed objects using a 2007 QuickBird image. These non-shadowed objects are then divided into vegetated and non-vegetated objects using a Normalized Difference Vegetation Index (NDVI). Through a rule-based classification using the height information from LiDAR data, vegetated objects are classified into grassland, shrubs and trees while non-vegetated objects are distinguished into low and high features. Low features are then separated into bare soil and transport units, again using a NDVI, while high features are classified as buildings and high crossroads using the shape of the objects (density). The 2007 shadowed objects are classified based on the spectral and spatial information of a 2005 QuickBird image, where shadows are in different directions. The developed methodology produced results with an overall accuracy of 87%. Misclassifications among vegetated features are due to the fact that the nDSM did not express the height for permeable features, while among non-vegetated features are due to temporal discrepancies between the DTM and the DSM, to different satellite azimuths in the 2005 and 2007 images and to unsuitable contextual rules.

1. INTRODUCTION

The extraction of large scale geographical information from very high resolution satellite images is an important research topic in urban studies, especially in areas with an elevated rate of urban changes, as a way to update the geographical information. One of the main Portuguese instruments of territorial management is the Municipal Director Plan (PDM-Master Plan) which has to be updated every ten years. However, in municipalities with great urban demands, such as the Lisbon municipality, such periodicity is not suitable. These PDM´s are produced at scales 1: 10 000 and 1:25 000, respectively, for urban and rural municipalities.

The analysis of urban areas demands for a high spatial resolution. Traditionally, the extraction of the required information at national mapping agencies has been performed based on the visual interpretation of extremely high resolution aerial photos, which is an expensive and time consuming process. Alternatively, high satellite resolution satellite imagery can play a role in the capture and maintenance of topographic information. However, the information that can be extracted from these images is useful to capture medium scale mapping features, being difficult to interpret most of the features that are of greatest interest in the update of large scale data (Holland *et al*., 2006). In what concerns the PDM's updating, the most relevant features are, in order of importance, built-up areas, other impervious surfaces such as concrete parking lots, sidewalks and asphalt roadways, vegetated areas and vacant land. Even though airborne and spaceborne imagery have been conventionally used for map compilation in updating processes, the casting shadows that dominate in the scenes acquired over dense urban areas and the leaning of buildings and other elevated features due to the geometry of acquisition and the heterogeneity of the spectral information can cause some inevitable problems (Vu *et al*., 2004).

Light Detection And Ranging (LiDAR) is a relatively new remote sensing technique that is revolutionizing topographic terrain mapping (Alexander *et al.*, 2009). The potential of surface-cover height extracted from multiple-return LiDAR data for urban areas analysis and building extraction has been shown by many authors (Vu *et al.*, 2004; Sohn and Dowman, 2007; Alexander *et al*., 2009; Chen *et al*., 2009; Zhou *et al*., 2009). Priestnall and Glover (1998) stated that the incorporation of building heights offers important extra information over and above that offered by optical sensors alone. In fact, Chen *et al*. (2009) concluded that the combination of high spatial resolution imagery, such as the QuickBird imagery, and LiDAR data can improve urban features classification accuracy, since the former provides ample spectral and textural information, while the latter offers good geometry for urban core building delineation.

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The aim of the research described in this study is to examine the potential of high resolution satellite imagery to derive a sub-product with less detailed thematic and geographic information but with a higher temporal resolution. It is expected that this more general level of information should be able to fulfil the need to detect, more regularly, significant changes to features in urban environments. To achieve this, a multi-source and multi-temporal dataset, including QuickBird imagery and LiDAR data, is used to develop an object oriented classification method to produce updated thematic cartography for municipal activities.

This manuscript is organized into the following five sections. Section 2 presents an overview and references to other studies related with the urban features extraction from high resolution imagery and LiDAR data. In section 3, we describe the case study area, the characteristics of the dataset and the software used in this study. Section 4 is concerned with describing the developed methodology. The next section, section 5, describes and discusses the results of this research. Finally, in section 6 some conclusions are drawn.

2. HIGH RESOLUTION REMOTE SENSING OF URBAN AREAS

The availability of images acquired by the current generation of high spatial resolution satellite sensors has contributed for new applications, especially for detailed urban areas maps at large scales. Even though their spatial resolution enables the identification of urban and sub-urban objects, these images are difficulty to classify on a pixel-by-pixel basis due to their high level of information (Van der Sande *et al*., 2003). Images of urban areas contain a complex spatial set of spectrally distinct land feature types, which require important spatial/semantic information for their classification. In these cases, object-oriented image classification algorithms are recommended because the information necessary to interpret those images is represented by image objects and their mutual relationships (Gamanya *et al*., 2007).

Another limitation on the use of high spatial resolution images is related to the existence of shadows cast by elevated urban objects, particularly buildings. These shaded areas are usually left unclassified or simply classified as shadows (e.g., Shackelford and Davis, 2003), resulting in significant loss of land features information. One possible approach to overcome this problem is to use spatial information, such as adjacency relations, for the classification of shaded areas in this kind of images (e.g., Yuan and Bauer, 2006; Zhou and Troy, 2008). Object-oriented classification algorithms, that consider not only the spectral information but also several other image object features, such as shape, texture and spatial context, may be used to improve the classification in urban areas (Benz *et al*., 2004; Zhou and Troy, 2008). Zhou *et al*. (2009) used both the spatial relations to neighbouring objects and the Normalized Difference Vegetation Index (NDVI), to distinguish “low shadows” into grass and pavement and “high shadows” into trees and buildings. Alternatively, shadows may be classified by replacing the shadowed pixels by non-shaded pixels of the same region from another image acquired at a different time as proposed by Zhou *et al*. (2009).

Complementarily, altimetry data from LiDAR may be helpful in the discrimination of image features of the same material at different heights, such as concrete buildings and road/vacant land in urban areas (Madhok and Landgrebe, 1999; Gamba and Houshmand, 2002; Chen *et al*., 2009; Zhou *et al*., 2009). However, LiDAR data itself is insufficient to discriminate between different features with the same height, such as buildings and trees (Vu *et al*., 2004). In such cases, spectral indices, such as the NDVI, can be used to first discriminate between vegetation and impervious surface and then at a low level of segmentation, the LiDAR data can be used to discriminate among features with different heights. As an example, using the height information obtained from the surface height model, Chen *et al*. (2009) were able to discriminate artificial features into crossroads, high buildings and low buildings, while Zhou *et al*. (2009) separated impervious surfaces into buildings and pavements.

3. STUDY AREA AND MATERIALS

3.1 Study area

The study area, located within the Lisbon Municipality (Figure 1), has a square shape with an area of approximately 570 ha (approximately 2.4 km x 2.4 km). This site was chosen because it contains the main features of interest for the municipality (buildings, other impervious surfaces, vegetated areas and vacant land) and also because LiDAR data were available for the area (LiDAR data extent is smaller than the area of the municipality of Lisbon). The west part of the study area is dominated by a dense urban area with a variety of building types and different kinds of transport units (roads, railway and associated land). The east part, although it contains some scattered building areas and roads with different widths, comprises a wooded area in the North, some vegetated areas, mainly belonging to a golf course, some shrub and/or herbaceous vegetation and bare soil. Water features are also present in the study area (within the golf course) but their area is insignificant when compared to the total area of the study site. Variations in the terrain are found in the study site, with altitudes ranging from 25 to 110 metres.

3.2 Data and software

The satellite data consist of two pan-sharpened QuickBird image dated 13 April 2005 and 11 March 2007, with a spatial resolution of 0.6 m. The sun azimuth and elevation of the 2005 image are 149°.6 and 57°.3, respectively, while for the 2007 image those values are 161°.4 and 46°.0, respectively. All images have been orthorectified with sub-pixel accuracy, using Rational Polynomial Coefficients (RPCs) with 29 GCP’s and validated with 22 checkpoints. For orthorectification, a Digital Terrain Model (DTM) was generated from the 1998 municipality vector cartographic map at scale 1:1 000 with a spatial resolution of 0.5 m. A 2006 LiDAR Digital Surface Model (DSM) with a 1-meter spatial resolution was provided by LOGICA, covering only partially the extent of the municipality of Lisbon. Elevation and intensity of the first and last pulse returns from a TopoSys II 83 kHz LiDAR instrument, flown on a helicopter, were recorded for each laser pulse, with an average measurement density of 20 points per m^2. The provided DSM was produced using the last pulse returns, meaning that only data from the surface that was last hit by the laser pulse was considered. In the case of buildings or other impermeable surfaces, the first and last returns will yield the same information. A surface cover height model (nDSM) was generated by subtracting the DTM from the DSM, to be used as ancillary data in the classification process. Orthorectified photographs acquired on 16 August 2007 were provided by the Portuguese Geographical Institute (IGP) and used to collect the reference data used for the accuracy assessment of the map. These images have four spectral bands in the blue, green, red and infrared wavelengths and 0.5 m spatial resolution. All data was converted to the PT-TM06/ETRS89 coordinate system and the vertical datum of the DSM and the DTM is the maregraph of Cascais. The Definiens Professional 5.0 software was used to conduct the object-oriented images analysis. Images orthorectification was undertaken in the PCI Geomatica V9.1 (OrthoEngine) since Definiens does not support those capabilities.

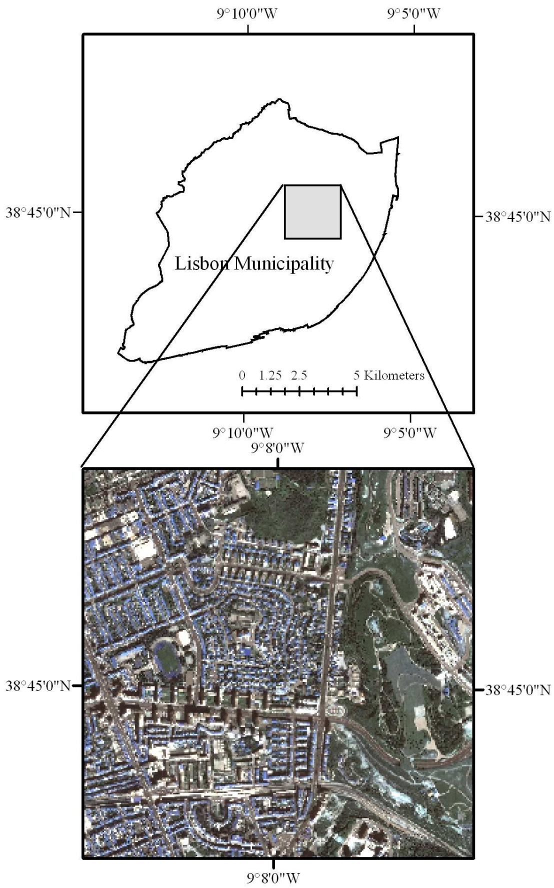

Figure 1. Study area (grey square): an urban area in the Municipality of Lisbon, Portugal

4. METHODOLOGY

A hierarquical object-based procedure was developed to classify a 2007 QuickBird image into seven classes (trees, shrubs, grass, buildings, transport units, bare soil and water). The dataset used to implement this procedure integrates a multitemporal set of QuickBird images and LiDAR elevation data. The hierarchical information extraction process was made up of three main steps. First, the dark objects (water and shadows) and non-dark object were separated. Then, the non-dark objects were classified using the 2007 QuickBird image. Finally, the dark objects were classified using the 2005 QuickBird image. In both of the classifications steps an identical classification approach was adopted. First, vegetation and artificial features are differentiated. Underneath vegetation class, grass, shrub and tree were extracted, while under the artificial class, road, building and bare soil were discriminated. As shadows could not be entirely recovered due to the acquisition geometry of the 2005 image, the common shadows between 2005 and 2007 were classified using contextual rules.

4.1 Image segmentation

Image segmentation is the process of dividing an image in non-overlapping parts in the image space (Schiewe, 2002). The Definiens Professional 5.0 software provides several possible image segmentation algorithms (Definiens, 2006). In this study the multi-resolution segmentation was adopted. This algorithm requires several inputs, such the scale parameter and the color and shape parameters. Those values were defined through trial-and-error and visual inspection for the two segmentations steps of the methodology. The 2007 QuickBird image segmentation was applied, with a scale parameter of 75, a color parameter of 0.9 and a shape parameter of 0.1, whilst the 2005 QuickBird image was processed at a finer scale of 25, the weights for colour and shape were kept as 0.9 and 0.1, respectively.

4.2 Water and shadow detection

Dark objects, that include both water and shadows, were extracted with a histogram thresholding method. A synthetic brightness image was initially computed though the NIR, red and green bands mean value and then a histogram of brightness based on pixel was analysed to determine an optimum threshold value for shadows and non-shadows (a threshold value of 180 was set). As mentioned by Zhou et al. (2009), it is assumed that this histogram is bimodal, with the lower part being occupied by the darker features (shadows and water). Once the dark objects also included water, a Spectral Shape Index (SSI) can be used to distinguish water from the black body mask (Dou and Chen, 2005). The threshold range for separating these two features was set in [134, 163].

4.3 Non-shadowed areas classification

The class hierarchy and its associated features and rules used for the classification of the 2007 QuickBird image are presented in Figure 2. Non-shadowed areas, identified previously in the first step of the methodology, were initially separated into two features, vegetation and non-vegetation features, using a NDVI. The NDVI was calculated with the formula NDVI = (NIR-Red)/(NIR+Red) and the threshold was set to 0.36, through pixel-based histogram analysis.

The non-vegetation features were then further divided, using the nDSM, in high (nDSM> 1.91 m) and low features (nDSM≤ 1.91 m). These high features were after separated into buildings and high crossroads using a shape function (Definiens, 2006). The density parameter, which is defined as the ratio between the object's area and its radius, was used because human constructions, in particular industrial and commercial areas, tend to have a higher density value (Navulur, 2007). The density range was set to [0.7, 5], being 5 the maximum value. Low features were next divided in bare soil and roads, using a "blue" NDVI, computed using the formula: bNDVI = (NIR-Blue)/(NIR+Blue). The threshold value used to discriminate both features was set as 0.15. Roads and high crossroads were merged as a unique class, named transport units, since only two high crossroads were observed in the 2007 image.

Three different features, trees, shrubs and grass, were discriminated under the vegetation features. This discrimination was achieved based on the nDSM standard deviation. As the DSM correspond to the last pulse data of LiDAR, the nDSM expresses only correctly the height of artificial features, because vegetated areas are permeable. Therefore, to search for residual difference in high between these three features, the standard deviation of the nDSM was evaluated and further used. The adopted threshold values for grass and trees were, respectively σnDSM≤ 0.6 and σnDSM≥ 2.17. Shrubs were identified by the in between values of the interval.

FIGURE 2

Figure 2. The hierarchical rule-based classification.

4.4 Shadowed areas classification

Shadowed areas were classified using the spectral and spatial information of the 2005 satellite image. In this case the adopted methodology is similar to the one described for the non-shadowed areas, with the exception that the threshold values differ slightly from the ones used for non-shadowed features in the 2007 image due to the fact that the images were acquired at different months and different years. Besides, the initial segmentation was performed at a finer scale in order to keep the parent-child relation between objects. However, this approach was not completely effective since the sun azimuth angles of both images were not significantly different. As a result of this, each shadowed area could not be entirely restored. To classify the remaining shadows, an alternative approach based on the relations to neighbour objects in the 2005 classification map had to be considered. The selected contextual rule was based on the "relative border to" function (Definiens, 2006), e.g. a shadow object with a relative border to a transportation unit ≥ 0.6 is classified as transportation unit; and a shadow object with a relative border to tree = 1 (i.e. totally surrounded) is classified as tree.

4.5 Accuracy assessment

For the accuracy assessment of the produced thematic map, a random stratified sampling method was used to prepare the ground reference data. This sampling method must be applied when there is a need to ensure a minimum sample size in each stratum to derive accuracy estimates for all classes presented in the map (Stehman, 1999). The individuals sample units were defined as polygons displayed on the classified image. Polygons are suitable for the accuracy assessment of maps generated through the use of image segmentation and object-oriented classification algorithms (Congalton and Green, 2009). A total number of at least 300 random polygons was planned to be sampled, with a minimum number of 50 samples per each map class, as proposed by Congalton (1988) for maps of less than 1 million acres in size and fewer than 12 classes. The class "water" was not considered in the accuracy assessment since it occupies less than 0.5 ha. Reference data was collected and labelled using the same classification scheme as the one used to generate the map. Since the classification scheme used is simple (with a few general classes), the reference label for each sample unit was derived by visual analysis of orthorectified aerial photographs acquired in 2007 with 0.5 m spatial resolution. Reference data was also collected on the ground and compared with the airborne data to verify the reference labels derived mainly for vegetated classes (trees, shrubs and grassland). The analysis of the accuracy assessment was done with an error matrix. An error matrix summarises the correct classifications and misclassifications in a contingency table format, with the rows designating the map labels and the columns the reference labels (Stehman and Czaplewski, 2003). Standard accuracy measures (overall accuracy, producer's and user's accuracy, as well as Kappa statistics) were derived from the classification results.

5. RESULTS AND DISCUSSION

Using the pixel-based shadow detection method together with the SSI method, most shadowed areas were correctly identified (91%). The lowest value of 90% was found for the user's accuracy of non-shadowed areas and for the producer's accuracy of the shadowed areas. The overall accuracy of the "water" class was determined by visual interpretation as being 100%. For some classes, such as trees and shrub, less than 50 samples were selected because they were not so representative in the study site, occupying only 4.6% and 8.7% of the total area, respectively. For the remaining classes, 50 or more samples were selected with a total of 385 validation samples. An overall accuracy of 87% was achieved for the object oriented classification results (Table 1). An extract of the final extracted seven objects is shown in Figure 3.

Classification accuracy is 89% both for trees and grass, while for shrubs its value is low, only 57%. Shrubs are overestimated on the final map, being confused mostly with grass but also with trees. In the case of vegetated areas the height information was of relative use, mostly due to the fact that the nDSM could not be directly used since it did not represent the height of vegetated features. Misclassifications of bare soil as grass were originated at the upper level of the hierarchical classification when vegetated and non-vegetated features were separated, and are verified in samples were the soil still has some sparse vegetation. Transport units being classified as grass is due to the inappropriate value obtained for the "relative border to" of a remaining shadowed object.

Classified data	Reference data						User acc. (%)
	B	Bs	Tu	Tr	Sh	Gs	
B	102	3					97
Bs		76	8			11	80
Tu		3	51				94
Tr				34		4	89
Sh				5	21	11	57
Gs		2	2		2	50	89
Producer's acc. (%)	100	90	84	87	91	66	
Overall accuracy: 87%; Kappa coefficient: 0.84							

Table 1. Error matrix and user's, producer's and overall accuracy and Kappa statistics for the produced map. B- buildings, Bs- bare soil, Tu- transport units, Tr- trees, Sh- shrubs and Gs- grass.

Buildings and transport units are the classes with the lowest commission errors, respectively 3% and 6%. For both classes the use of the nDSM was extremely helpful. Commission errors of bare soil as buildings are also explained by unsuitable "relative border to" values, but also by the existence of shadowed areas in 2007 that in the 2005 image were in fact buildings due to different satellite azimuth angles. In the 2007 shadows are in the NNW-direction and high features are leaning in the ENE-direction, while in the 2005 image high features are leaning in the WNW-direction. Misclassifications between bare soil and transport units are easily justified by the bNDVI threshold used to discriminate them.

FIGURE 3

Figure 3. A subset of the study area. (a) the original 2007 QuickBird imagery; (b) shadows identified by a pixel-based histogram thresholding method; (c) land cover classification obtained with the proposed methodology.

Misclassifications among features with distinct heights might also have been originated by some height inconsistencies found between the DTM and the DSM due to their large time gap. To avoid this kind of misclassifications, ancillary data should be acquired preferentially in the same year or, if not possible, with a time gap of less than a couple of years, especially in urban areas with an elevated rate of changes. A better discrimination among vegetated classes might have been achieved with the use of an nDSM obtained by the difference between a DSM, interpolated from the first pulse of raw LiDAR data, and a more up to date DTM.

6. CONCLUSIONS

Shadowed areas are a major problem in urban high resolution satellite imagery due to the high density of urban features. As the problem of shadowing causes reduction or total loss of spectral feature information, we have developed a methodology that provides a useful approach for the classification of shadows using this kind of imagery in urban areas. However, changes may occur in ancillary data acquired at different dates, which may introduce errors in the classification. A simple approach, such as a bimodal histogram splitting, combined with a Spectral Shape Index provided an efficient way of separating shadows from non-shadows. The use of a multitemporal set of QuickBird imagery with different acquisition geometries was useful in restoring the spectral information casted by urban features in the 2007 image. However, for this approach to be completely effective, satellite azimuths angles of both images should be similar while sun azimuth angles should be as opposite as possible. LiDAR data was crucial to separate features with different elevation values, especially for the non-vegetated features. Without this segmentation level it would have been extremely difficult to differentiate at a lower level those non-vegetation features into buildings, transport units and bare soil. LiDAR data was not very useful in the discrimination of vegetated features once the DSM, used to generate the nDSM, was interpolated from the last pulse of LiDAR returns.

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