EXTRACTION OF BUILDINGS FROM QUICKBIRD IMAGERY – WHAT IS THE RELEVANCE OF URBAN CONTEXT AND HETEROGENEITY?

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ABSTRACT:

The high frequency and scope of spatial changes in cities demands ways of expediting the production and updating of large-scale geographic information. For that purpose, current and future very high spatial resolution satellite imagery (VHR) and semi-automated object-based image analysis methods may be an advantageous alternative to classical data sources and methods, i.e., aerial photography and photogrammetry. At the same time, the urban environment is becoming more complex and heterogeneous, possibly turning the feature extraction process more challenging. While much research has focused on developing, adapting and applying these approaches, less attention has been devoted to the interplay of data source (imagery), feature extraction methods, and geographic characteristics of the area under analysis. Lisbon, Portugal, is both a historical and modern city having a dynamic landscape, where increasingly diverse urban forms and materials coexist. This complex reality is possibly causing the feature extraction process from imagery to become more challenging. This study tests the semi-automated extraction of buildings from a QuickBird image in several urban study areas in Lisbon having different characteristics, and explores the impact of the heterogeneity of these features in the extraction process. Spatial metrics and spectral response are used to characterize types of buildings present in the study areas. Results show that the study areas display different levels of heterogeneity even for the same type of building and suggest that the quality of the extraction is affected by more factors than the complex variations in color/tone, composition and spatial configuration of target features.

1. INTRODUCTION

The majority of municipal activities, namely in urban planning and management, have a geographic component. Most large cities experience a high frequency and scope of spatial changes, which demand ways of expediting the production and updating of large-scale geographic information. In Portugal, this is legally required to support the Municipal Master Plans. For that purpose, current and future very high spatial resolution satellite imagery (VHR), due to their availability, wide coverage, and cost, may be an advantageous alternative to classical data sources and methods, i.e., aerial photography and photogrammetry (Ehlers, 2007).

The nature of this recent data source, volume of data, and expanding range of applications has been driving the development of advanced semi-automated geographic object-based image analysis (i.e. GEOBIA) (Hay and Castilla, 2008) methods for efficient feature extraction. There are now several commercial-off-the-shelf software packages which are increasingly user-friendly. Still, to be operationally adopted by municipalities, feature extraction should be reliable, have clear procedures and parameters to facilitate insertion into a mapping work-flow, and conform or approach quality standards typical of large-scale mapping. Therefore bringing GEOBIA approaches into the operational mapping domain remains a challenge and should probably be a 'hot' research topic in the field in addition to the four topics recently listed by Blaschke (2010).

At the same time, the overall urban environment is becoming more complex and heterogeneous, possibly turning the feature extraction process more challenging. In old cities, the historical process of urbanization originates urban features which vary widely regarding age, condition, spatial composition and configuration. While much research has focused on developing, adapting and applying these approaches, less attention has been devoted to the interplay of spectral data source (imagery), feature extraction methods, and geographic characteristics of the area under analysis.

Originating in landscape ecology, spatial metrics can be employed to measure the heterogeneity of landscapes at different spatial scales based on categorical patches or elements. Herold et al. (2003a) have used spatial metrics and texture to analyze and differentiate urban land uses in an urbanized coastal area of California, USA and concluded that these metrics contribute the most information to image

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classification, despite confusion among different residential land-use types.

The work presented in this paper takes place in the context of the exploration of VHR satellite imagery and new methods as an alternative source of geospatial information for large scale mapping to assist urban planning and management in Lisbon, Portugal. The present effort aims at testing the semi-automated extraction of different building types from areas with diverse characteristics, and investigating the impact of the heterogeneity of these features and the urban context in the extraction process.

2. STUDY AREA AND DATASETS

2.1 Study area

Lisbon is both a historical and modern city having a dynamic and complex landscape. Four study areas were selected in different parts of the city, to represent the diversity of urban character. The areas have a square shape and the same size of 64 ha (800 m X 800 m) (Figure 1).

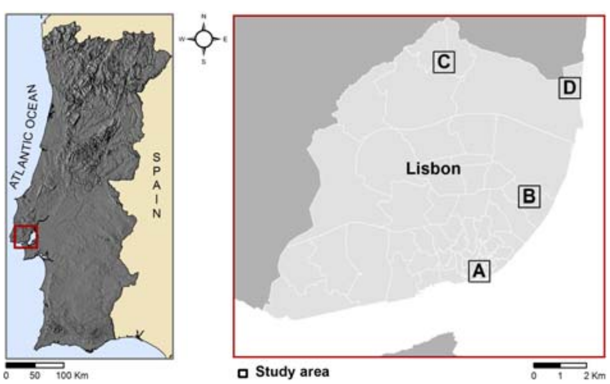

Figure 1. Location of the study areas

Study area A (Baixa) is located in the slow-changing old historical district (i.e., downtown): the street network is dense and most of the area is built-up. Study area B (Madre) is located in the oriental part of the city and has a very heterogeneous land use, including built-up, parks, agriculture and vacant land; buildings' functions range from residential (single and multi-family housing), to industrial, utilities, and schools. Study area C (Alta) is a new residential area under development, with on-going construction of parks, roads, and apartment buildings. Study area D (Expo) corresponds mostly to a former heavily industrial area (brown fields) which has been developed since being selected to host the 1998 Lisbon World Exposition (Expo '98).

The four study areas are quite distinct, with their current urban morphology and majority of buildings originating in different periods (Table 1).

Study Area	Urban Morphology	Majority of Buildings
A-Baixa	<= 18^{th}	18^{th}, 19^{th}
B-Madre	<= 19^{th}, 20^{th}	20^{th}
C-Alta	21^{st}	21^{st}
D-Expo	20^{th}	20^{th}

Table 1. Main periods (centuries) determining current urban layout of the study areas

2.2 Datasets

The spatial database includes spectral, altimetric, and planimetric data sets. A QuickBird (QB) image was acquired in April 14, 2005 with an off-Nadir angle of 12,2º. The image has a spatial resolution of 2,4 m in the multispectral mode and 0,6 m in the panchromatic mode, and a radiometric resolution of 11 bits. Altimetric data included a normalized Digital Surface Model (nDSM) for 2006 obtained from combining a LiDAR-derived DSM with a Digital Terrain Model, both at 1 m resolution. Planimetry included a detailed reference map of building roofs outlines and types, produced by an independent interpreter using visual analysis of the imagery and ancillary data.

Pre-processing of data has included orthorrectification and pansharpening of imagery in PCI Geomatica and production of the nDSM grid. All data sets were geometrically corrected to a common projected coordinate system (PT-TM06/ETRS89). Still, there was some mis-registration between the QuickBird and the nDSM data sets on building's roofs (relief displacement) due to the significant off-Nadir angle of the image. For more details on this stage see Santos et al. (2010).

3. METHODOLOGY

The approach involved extraction of specific classes of buildings and its quality assessment, computing spatial metrics and image variance for each study area and building class, and analyzing the results.

3.1 Feature extraction

Since our goal was to analyze the heterogeneity of building features in the study areas, and satellite imagery capture their roof, a typology of buildings' roofs was defined based on their main material and its color/tone/reflectance, the primary elements in image analysis (Estes et al., 1983). The following building classes were used: 1-Red tile roof, 2- Dark tile roof, 3-Light tin roof, 4-Dark tin roof, 5-Fibrocement roof, 6-White roof, and 7-Other roofs.

Extraction of building classes (polygons) from the imagery was performed using Feature Analyst 4.2 (VLS), as an extension for ArcGIS (ESRI). Feature Analyst (FA) is a *GEOBIA* application that conducts an internal "hidden" segmentation of the image that allows classifying and extracting only those features belonging to the class of interest (Optiz and Blundell, 2008).

The training parameters that resulted in the best extraction of each building class in each study area are listed in Table 2.

Study Area	Bldg. Class	Training Features	Pattern	Width	Aggreg.
A	1	49	Manh.	13	11
	2	49	Manh.	13	11
	3	4	Manh.	9	70
	5	4	Manh.	9	70
	6	3	Manh.	11	90
B	1	24	Manh.	5	10
	3	1	Manh.	5	100
	4	5	Manh.	9	70
	5	7	Manh.	5	100
	6	2	Manh.	5	10
C	1	7	Manh.	13	200
	5	4	Manh.	13	200
	6	6	Manh.	9	80
D	1	9	Manh.	5	80
	5	14	Manh.	13	100
	6	8	Manh.	13	100

Table 2. Parameters used for feature extraction

Not all building classes were present or significant enough (i.e., having more than 10 features) for extraction in each study area. Extracted features were not generalized or squared up prior to accuracy assessment.

Each building class was extracted independently using the pansharpened QuickBird image as main input, and the nDSM as ancillary elevation. Although individual adjacent buildings can be identified visually in the image and used as training areas, due to the combined limitations of extraction algorithms and image spatial resolution, FA can only retrieve building blocks of the same class. Building blocks equal buildings for non-contiguous buildings.

For assessing the quality of the feature extraction stage, and in the absence of a compatible and updated official map, a reference map of building blocks was created by an independent interpreter using visual analysis and manual digitizing over the pansharpened image, with the assistance of ancillary data (e.g. orthophotos). All the discernible buildings, without limits of size or shape, were digitized and classified as belonging to one of the seven classes.

Thematic quality assessment was exhaustive (i.e., by census) and conducted independently for each class using ArcGIS 9.3 (ESRI). It was based on analysis of spatial overlap between classified and reference map for each building class, in vector format: percent overall accuracy is obtained by dividing the area of intersection of both datasets by the area of union, while the proportion of non-overlapping features from the reference map stands for error of omission and the proportion of non-overlapping features from the classified map stands for error of commission (Freire et al., 2010). Because the independently-extracted datasets for different building classes can overlap, an object-based overall thematic accuracy for study areas can be obtained by computing an average value among extracted classes weighted by the actual number of features (in the reference dataset).

3.2 Spatial metrics and spectral response

Although some metrics are highly correlated to one another and can be redundant, a large set of spatial metrics (Table 3) was selected and computed as patch-based indices for each building class in the reference dataset in order to characterize the buildings present in the study areas and assemble a database.

Indicator	Acronym	Units
Number of features	NoF	Number
Percentage of features	No %	Percent
Feature density	Fdens	no. per ha
Percentage of landscape	PL	Percent
Mean feature size	AREA MN	m2
Area standard deviation	AREA STD	m2
Shape Index	SI	--
Perimeter-Area Ratio	PAR	m per m2
Fractal Dimension	FD	--
Nearest Neighbor Mean Euclidian Distance	ENN MEAN	m
Richness	R	--
Diversity Index	Div	--
Evenness Index	Eve	--
Dominance	D	--

Table 3. List of spatial metrics computed

The metrics are used to quantify the spatial heterogeneity at two levels in each study area: a) the building block class level, and b) the landscape level, using overall values for each study area. Calculating metrics for typologies of building roofs represents a one-level increase in the urban analysis scale when compared with the generic class "buildings" analyzed by Herold et al. (2003a).

The metrics were calculated in ArcGIS 9.3 in vector format for the reference building blocks. The more complex indicators were computed using the V-LATE 1.1 extension tool (Lang and Teide, 2003). Shape Index, Perimeter-Area Ratio and Fractal Dimension give indications about landscape configuration, while Richness, Shannon's Diversity and Evenness Indices, and Dominance are examples of landscape composition indicators. More details on these metrics can be found in O'Neill et al. (1988) and Herold et al. (2003).

In order to study the heterogeneity of the spectral response within each building type, its variance for the image bands was computed and analyzed. For the pansharpened image pixels within each feature class and study area, the standard deviation (Std.) of each band's Digital Numbers (DNs) was computed and averaged for the four bands.

4. RESULTS AND DISCUSSION

4.1 Feature extraction

In study areas A and B five classes were extracted, while in study areas C and D only three had significance to be extracted. Figure 2 illustrates results of extraction for buildings with tile roofs in study area A.

Figure 2. Example of extracted features in study area A-Baixa

Results of quality assessment (Table 4) show that thematic accuracies varied significantly within and among the study areas, even for the same building class. Accuracies were generally low for all classes other than buildings with tile roofs. This class was the most-consistently extracted. Accuracy for buildings with white roofs (6) had the widest range, being lowest in study areas A and C, while attaining the highest value in area D. Some roof types, while being semantically different for a human interpreter, are not sufficiently distinct spatially and spectrally for an automated classification. Most roof types are spectrally similar to patches of other urban features such as roads and bare ground (Herold et al., 2003a; 2003b), and there is not sufficient contrast between the object and its background, a requirement for its correct detection and delineation (Jensen and Cowen, 1999).

Study Area	Bldg. Class	Overall Accuracy	Error Omission	Error Commission
A	1	70,1	26,1	6,8
	2	70,1	26,1	6,8
	3	36,8	40,9	50,6
	5	26	70,7	31,2
	6	19,2	56,3	74,5
B	1	73,2	22,1	7,5
	3	43,5	56,5	4,8
	4	46,8	32,6	39,6
	5	46,3	51,6	10,2
	6	67,9	27,1	9,2
C	1	83,6	6,0	11,7
	5	46,8	6,5	51,6
	6	29,9	32,2	65,1
D	1	65,5	13,8	26,9
	5	32,6	37,7	59,1
	6	86,9	12,1	1,6

Table 4. Results of thematic quality assessment (%) for each building class by study area

Building feature classes tend to be significantly undermapped, especially in study areas B and D (omission error higher than commission). However, buildings are significantly overmapped in study area C (commission error higher than omission), due to confusion with bare ground, highway viaduct and other materials because of on-going construction at the time of image acquisition.

In study areas A and B some buildings are partially covered by trees and in area B there are shipping containers that are mis-extracted as buildings.

4.2 Spatial metrics and spectral response

Some of the spatial metrics obtained for each building class in each study area are shown in Tables 5 and 6. Results reveal that most metrics vary widely between study areas for the same feature class. The widest variations occur for buildings with red tile roofs, the most prevalent in Lisbon. Although their density is highest in area B, their prevalence (PL) is highest in area A, where their mean size (Area MN) is greatest, despite showing great variation (STD). Highest accuracy was obtained in area C, where the boundaries are simpler and more regular (lowest FD) and distance between buildings is greatest (ENN MEAN).

Metrics for fibrocement roofs also display significant variation: their presence is much more significant in study area B (due to industrial land use), although their average size is quite smaller than in the other areas; the Shape Index indicates that these buildings are more compact in A than in C (new area, long building blocks), while their boundaries are more irregular in B (higher FD).

White roofs have similar densities (Fdens) but are much more prevalent and much larger on area D, where they are also much more compact (highest SI) and have simpler boundaries. This may contribute to their high accuracy in this area.

Bldg. Class	Study Area	NoF	Fdens	PL	Area MN
Red tile roof	A	181	2,8	33,4	1180
	B	345	5,4	9,6	178
	C	33	0,5	3,2	627
	D	51	0,8	2,6	328
Dark tile roof	A	13	0,2	1,3	643
	B	7	0,1	0,1	108
Light tin roof	A	23	0,4	1	288
	B	31	0,5	0,7	148
Dark tin roof	A	2	0,03	0	125
	B	20	0,3	0,7	214
Fibrocement roof	A	56	0,9	2,8	323
	B	161	2,5	4,8	192
	C	11	0,2	1,8	1037
	D	47	0,7	24,2	936
White roof	A	16	0,3	0,5	199
	B	32	0,5	0,8	169
	C	13	0,2	1,4	671
	D	22	0,3	14,5	4223
Other roofs	A	5	0,1	0,1	150
	B	3	0,05	0,1	125
	C	4	0,1	0,2	326

Table 5. Spatial metrics for each building class by study area

Bldg. Class	Study Area	Area STD	SI	FD	ENN MEAN
Red tile roof	A	1873	1,65	1,6	4,8
	B	231	1,32	1,7	4,5
	C	523	1,44	1,56	22,9
	D	332	1,41	1,59	9,3
Dark tile roof	A	621	1,5	1,61	61,4
	B	106	1,19	1,76	84,5
Light tin roof	A	335	1,27	1,59	37,3
	B	365	1,35	1,93	37,8
Dark tin roof	A	96	1,5	1,79	774,6
	B	375	1,34	1,78	23,5
Fibrocement roof	A	623	1,31	1,65	16,1
	B	535	1,39	1,79	13,1
	C	704	1,59	1,56	51,3
	D	2412	1,45	1,59	24,9
White roof	A	265	1,46	1,71	68,4
	B	228	1,26	1,76	39,2
	C	1373	1,58	1,68	40,5
	D	5978	1,68	1,53	44,7
Other roofs	A	94	1,22	1,77	221,8
	B	84	1,23	1,81	260,8
	C	408	1,29	1,64	213,7

Table 6. Spatial metrics for each building class by study area (cont.)

Tables 7 and 8 show overall (weighted) accuracy and spatial metrics for all buildings in each study area (landscape level). Accuracies are relatively low and differences are not very significant. Accuracy was highest in areas B and C, and lowest in areas A and D. The latter areas have the largest variation of building sizes (AREA MN), while the former have the lowest. Buildings are the least compact in area A. The small size of buildings in study area B probably contributes to their undermapping (omission).

Relation to composition metrics does not appear evident: the area with lowest accuracy displays significantly lower Diversity, Evenness, and highest Dominance. Results suggest that the success of extraction may be more related to spatial configuration of features than to spatial composition of the landscape.

Study Area	Overall Accuracy	R	Div	Eve	D
A	56,1	7	0,62	0,32	1,33
B	65,7	7	1,15	0,59	0,80
C	64,2	4	1,14	0,82	0,25
D	56,5	5	1,29	0,8	0,32

Table 7. Overall accuracy and spatial metrics for all buildings in each study area (landscape)

Study Area	NoF	AREA MN	AREA STD	SI	ENN MEAN
A	296	847	1559	1,53	24,3
B	599	180	350	1,33	13,2
C	61	690	826	1,49	44,3
D	162	1120	2897	1,43	27,4

Table 8. Overall accuracy and spatial metrics for all buildings in each study area (landscape)

Table 9 illustrates variation in roof's spectral response by showing the mean Standard deviation of image DNs for each building class per study area.

Study Area	Bldg. Type/Class						
	1	2	3	4	5	6	7
A	128	80	265	68	118	175	126
B	114	71	157	72	106	228	87
C	100	-	-	-	116	166	113
D	115	-	63	-	183	163	223

Table 9. Mean Std. of image DNs for each building class by study area

It is building class 3 (light tin roof) that exhibits the smallest (area D) and greatest (area A) variations in spectral response. For class 1, variation is smallest in C, where its accuracy is highest. Class 6 also achieves its highest accuracy in area D where its variation is smallest, and lowest accuracy where variation is greatest.

These results, although preliminary, suggest some degree of dependence of accuracy on lower variance of features' spectral response or color.

5. CONCLUSIONS

The present work is an exploratory attempt at assessing the heterogeneity of feature types and studying the relevance of the urban context in the framework of semi-automated extraction of buildings from VHR satellite imagery for the purpose of urban planning and management.

Typical building classes from four study areas in Lisbon are delineated from a QuickBird image using automated feature extraction. Heterogeneity of building features is investigated using spatial metrics and variance in spectral response at the level of the building block. The analysis is focused on distinct types of roofs of buildings present in the study areas. Results show that thematic accuracy and spatial metrics of different building types vary significantly within the same study area and also among different study areas for the same semantic class of building. Roof types display different levels of heterogeneity.

Results suggest that the spectral context and spatial configuration of target features may be an important factor for the success of automated extraction. However, the quality of the extraction appears to be affected by more factors than the complex variations in reflectance, composition and spatial configuration of target features. Although the extraction's accuracy is not linearly related to the heterogeneity of features, the complexity and heterogeneity of such an historical and dynamic city make the automated extraction of buildings very challenging. Extraction of buildings having similar roofs is further complicated by the different solar illumination of roof gables at time of image acquisition.

Future developments include the inclusion of additional study areas (E was selected) as well as more quantitative analysis of spatial metrics. Measures of texture will be explored and the additional land cover context should be considered. Socio-economic variables from the census could be added to the spatial analysis to further characterize the different areas.

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