Automated Extraction of Buildings from Aerial LiDAR Point Cloud and Digital Imaging Datasets for 3D Cadastre - Preliminary Results

Pankaj Kumar[1*], Alias Abdul Rahman[1] and Gurcan Buyuksalih[2]
[1]Department of Geoinformation
Universiti Teknologi Malaysia
81310 Johor Bahru, Malaysia
pankajkumar@utm.my, alias@utm.my
[2] BIMTAS, IBB, Istanbul, Turkey
gbuyuksalih@yahoo.com

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SUMMARY

The demand for accurate 3D mapping of buildings has increased due to the spatial detail required by engineers, architects and city planners. An accurate information about location and dimension of building features is important for cadastral, city modeling, infrastructure mapping and safety analysis in an urban environment. LiDAR technology provides rapid, continuous and cost effective capability to acquire 3D geospatial information. In this paper, we present an automated approach for extracting building features from integrated aerial LiDAR point cloud and digital imaging datasets. Our approach is based on the assumption that the LiDAR data can be used to distinguish between high and low rise objects while the multispectral dataset can be used to filter out vegetation from the data. We make a use of LiDAR elevation and multiple echo attributes to extract building objects. Morphological operations are applied to the extracted building objects in order to complete their shapes and remove noise. We tested our automated buildings extraction approach on aerial LiDAR point cloud and digital imaging datasets of Istanbul city. The successful extraction of building objects validates our automated approach.

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[1]Department of Geoinformation
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81310 Johor Bahru, Malaysia
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[2] BIMTAS, IBB, Istanbul, Turkey
gbuyuksalih@yahoo.com

1. INTRODUCTION

3D extraction of buildings is required for many applications such as cadastral, city modeling, infrastructure mapping and urban growth analysis. Moreover, an accurate information about location and dimension of building features provides crucial input for the fire-safety analysis and managing other hazards in an urban environment. Traditionally, building boundaries are delineated based on manual or semi-automated reconstruction from close-range and satellite images. These processes are time-consuming and limited to 2D reconstruction of building objects. The lack of automated methods can be attributed to problems in finding an appropriate information from the data and the complexity in the scene (Elberink, 2008).

Advances in geospatial data acquisition techniques have transformed the concept of 2D building modeling to 3D. Light Detection And Ranging (LiDAR) enables 3D modeling of real world environment by measuring the time of return of an emitted light pulse (Kumar et al., 2013). Laser scanning systems use this technology to acquire an accurately georeferenced set of highly dense LiDAR point cloud data (Kumar, 2012). These systems provide high level of automation during data acquisition and have an ability to capture data beneath tree's canopy. The applicability of laser scanning systems continue to prove their worth in geospatial mapping due to the rapid, continuous and cost effective 3D data acquisition capability (Barber et al., 2006). LiDAR data records a number of attributes including elevation, intensity, pulse width, multiple echo and range information, all of which can be used for extracting various features (Kumar et al., 2015). The methods developed for segmenting LiDAR data are mostly based on the identification of planar surfaces and the classification of point cloud data based on its attributes (Vosselman, 2009).

Automated extraction of building objects has been a topic of intensive research since last few years. Several approaches have been developed over the past decade for extracting urban building features from LiDAR data. Mumtaz et al. (2009) developed a semi-automated approach for extracting building objects from the integration of airborne LiDAR and digital imaging datasets. In their approach, Normalized Digital Surface Model (NDSM) was generated from LiDAR and a Normalized Differential Vegetation Index (NDVI) was developed from digital image. Both the NDSM and NDVI values were thresholded and then morphological operations were applied to binary image for extracting building features.

However, in their approach, some of the large vehicles and industrial installations were incorrectly identified as buildings while smaller buildings were missed. Oda et al. (2004) proposed a method to extract building features from aerial LiDAR data in which Digital Surface Model (DSM) was segmented and then Hough transformation was applied for extracting building boundaries. Finally, 3D building model was created by attaching vertical walls from aerial image to each of the extracted building polygon. The proposed method did not addressed the problem of extracting inclined roof. Pu et al. (2006) presented an approach to automatically extract building features from terrestrial laser scanning data. LiDAR point cloud was segmented using the planar surface growing algorithm and then several human-knowledge driven feature constraints such as size, position, direction and topology were applied to extract building features. Mancini et al. (2009) used multi-source aerial LiDAR and multispectral dataset to automatically extract urban building and road objects. They involved multi-class supervised pixel classification using adaptive boosting algorithm to classify buildings, grass, land and tree objects. Finally, filtration and Hough transformation techniques were applied to extract linear road and roundabout features. Rutzinger et al. (2009) extracted vertical walls from mobile and airborne laser scanning data. A region growing segmentation technique based on 3D Hough transform was applied to extract planar surfaces from point cloud data and then the extracted segments were analyzed based on their inclination, size and dimension.

Most of the approaches developed for extracting buildings require semi-automated or manual intervention. The developed methods are also associated with the misclassification of large vehicles, trees and other features as building objects. There is a need to develop an operational and automated approach for extracting building features. LiDAR data provides elevation, intensity, pulse width and multiple echo attributes which can be a useful source of information for extracting building objects. The integration of multispectral digital images with LiDAR data will provide more efficient and accurate extraction of buildings. The use of LiDAR data provides to distinguish between high and low rise objects while multispectral data helps to distinguish canopies from the building objects. In this paper, we present some preliminary results based on automated extraction of building objects from the integration of aerial LiDAR and multispectral digital imaging datasets. In Section 2, we detail our methodology to extract buildings while in Section 3, we test our approach on aerial LiDAR and multispectral digital imaging dataset. Finally, we discuss the test results and make conclusions in Section 4.

2. METHODOLOGY

Our methodology is based on the integration of aerial LiDAR and digital imaging dataset to extract buildings. A workflow of the automated building extraction approach is shown in Figure 1. We make a use of digital imaging dataset to remove canopies from the data. The available multispectral digital image consisted of blue, green and red bands which represent brightness information of the targets. We utilize a low reflectance property of the

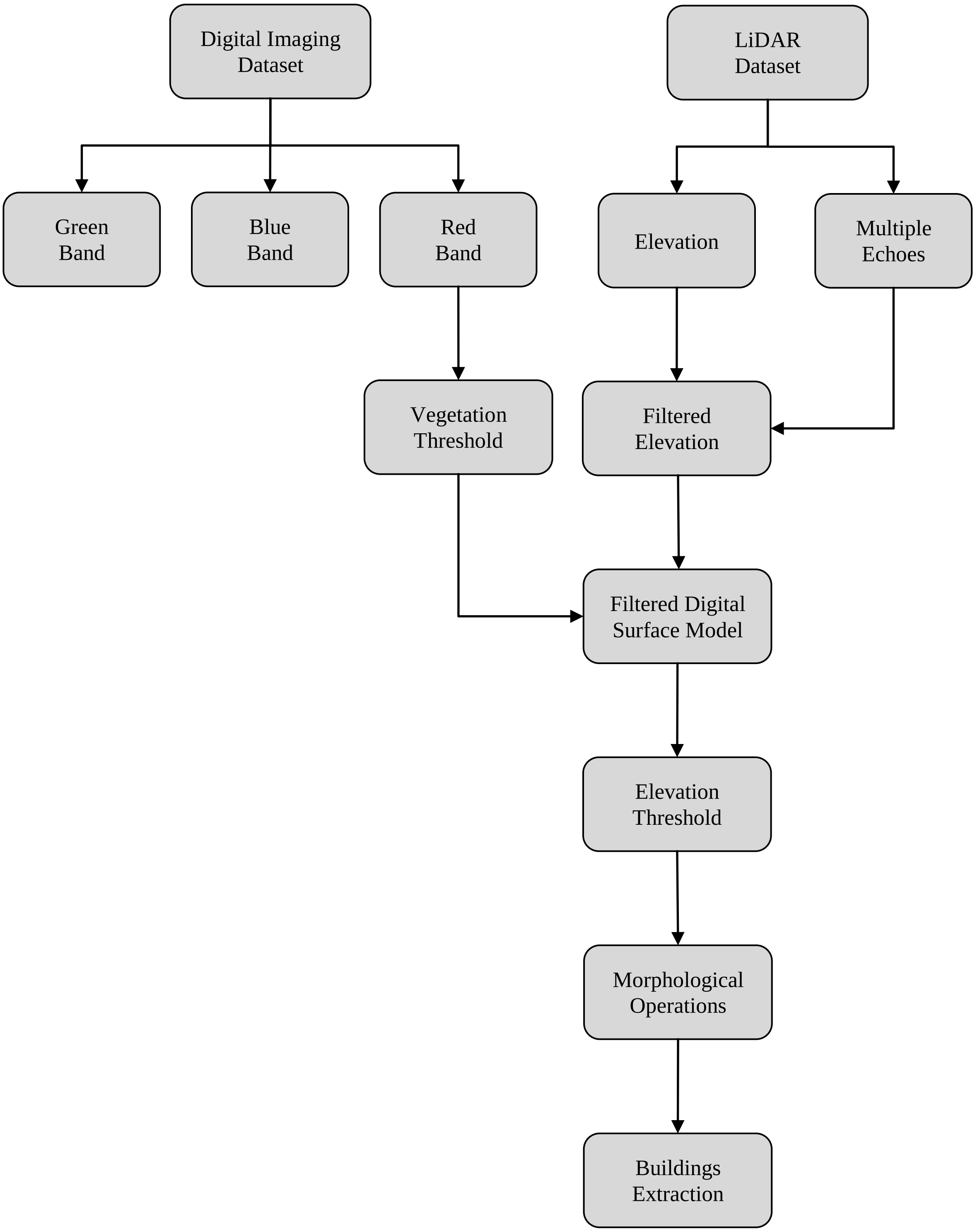

Figure 1: Automated buildings extraction approach.

vegetation in the red band to suppress them in the data. We apply empirically estimated T_1 threshold value to the red band image in order to remove the vegetation area.

LiDAR data provides multiple echo information which refers to multiple return of echo pulses from the targets. We filter out multiple reflected points and retain those points that record a single reflection. These single return reflection points belong to buildings, roads and other solid objects. The filtered points are used to generate Digital Surface Model (DSM) using the maximum elevation value of points within the cell while natural neighborhood interpolation method is used to estimate values for cells that do not have points within their extent. We use the thresholded red band image to remove vegetation area from the DSM. We apply empirically estimated T_2 threshold value to the DSM in order to remove ground level objects such as roads, parking areas etc. and retain high rise building features in the data. In order to complete the extracted buildings and remove noise that is introduced through the use of thresholding, we make a use of binary morphological operations. The thresholded DSM is converted into a binary image and is processed using morphological operations. We apply the morphological opening operation in which the binary image is eroded followed by their dilation while the morphological closing operation is applied by dilating the binary image followed by their erosion. In the dilation operation, a binary matrix element is used to dilate the image pixels and in the erosion operation, a binary matrix element is used to erode the image pixels (Kumar et al., 2014). Thus, the morphological operations applied to the binary image are able to extract inherent shapes of the building objects and to remove noise. Finally, contour boundary of each building object is identified and then LiDAR points inside each boundary are estimated to provide 3D generation of extracted building objects.

3. EXPERIMENTATION

We tested our automated building extraction approach on aerial LiDAR and multispectral image datasets of Istanbul city covering 89.76 Km^2 which was acquired in October, 2012. The multispectral image consisted of three bands i.e. red, blue and green with ground sampling distance of 0.1 m and 8-bit radiometric resolution. The LiDAR data consisted of 2647912 points with 0.18 m spacing. The point cloud was associated with elevation, intensity and multiple echo attributes. The empirically estimated $T_1 = 130$ threshold value was applied to red band image in order to remove vegetation. After filtering out multiple reflected points, the LiDAR data consisted of 2376200 points. The DSM was generated from the maximum elevation value of filtered points with 0.1 m cell size. We applied the empirically estimated $T_2 = 45$ threshold value to the DSM. The morphological opening and closing operations were applied using 3x3 matrix element. The tested multispectral image is shown in Figure 1(a) while the automated extracted 2D and 3D building objects are shown in Figures 1(b) and 2 respectively.

Figure 2: (a) Input multispectral image and automated extracted (b) 2D building objects.

Figure 3: Automated extracted 3D building objects.

4. DISCUSSION & CONCLUSION

Our automated approach was able to successfully extract the building objects from aerial multispectral digital imaging and LiDAR point cloud datasets. Some of the building objects along the lower-left side of the data were missed while some of the roads were extracted along the middle-right side of the data as false positive as seen in Figure 2(b). There is a need to validate these extraction results with respect to the ground truth. We used red band in the multispectral image to remove canopies from the data however, this information was not adequate. The use of both the near infra red and red bands would provide us to estimate Normalized Differential Vegetation Index (NDVI) which would be more efficient in removing vegetation areas from the data. The use of multiple echo attribute in the LiDAR data was further helpful in retaining the points that belong to buildings, roads and other solid objects. LiDAR data provides intensity attribute that represents the maximum amplitude of a reflected pulse. Intensity values can be used to differentiate buildings from other terrain objects. The minimum elevation value of points within the cell can be used to generate Digital Terrain Model (DTM) which can be further used to estimate Normalized Differential Surface Model (NDSM). NDSM values can be more efficiently used to remove ground level objects and retain building objects as they represent absolute height values of the terrain objects. The opening and closing morphological operations were applied to complete the shapes of extracted buildings and remove noise. There is a need of their inclusive use in which the dimensions of the extracted objects can be used to remove non-building objects. This research study presents preliminary results for extracting building objects from integrated aerial LiDAR point cloud and digital imaging datasets. In future, we intend to develop more comprehensive approach for automated and operational extraction of building objects.

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REFERENCES

Barber, D., Mills, J. and Smithvoysey, S. (2008). Geometric validation of a ground-based mobile laser scanning system. ISPRS Journal of Photogrammetry and Remote Sensing, 63 (1), pp. 128-141.

Elberink, S. O. (2008). Problems in automated building reconstruction based on dense airborne laser scanning data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 37 (XXX), pp. 93-98.

Kumar, P. (2012). Road features extraction using terrestrial mobile laser scanning system. National University of Ireland Maynooth, http://eprints.maynoothuniversity.ie/3995, 300 p., 25-January-2015.

Kumar, P., McElhinney, C. P., Lewis, P. and McCarthy, T. (2013). An automated algorithm for extracting road edges from terrestrial mobile LiDAR data. ISPRS Journal of Photogrammetry and Remote Sensing, 85, pp. 44-55.

Kumar, P., McElhinney, C. P., Lewis, P. and McCarthy, T. (2014). Automated road markings extraction from mobile laser scanning data. International Journal of Applied Earth Observation and Geoinformation, 32, pp. 125-137.

Kumar, P., Lewis, P., McElhinney, C. P. and Rahman, A. A. (2015). An algorithm for automated estimation of road roughness from mobile laser scanning data. The Photogrammetric Record, 30 (149), pp. 1-16.

Mancini, A., Frontoni, E. and Zingaretti, P. (2009). Automatic extraction of urban objects from multi-source aerial data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 38 (3/W4), pp. 13-18.

Mumtaz, S. and Mooney, K. (2009). A semi-automatic approach to object extraction from a combination of image and laser data, International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 38(3/W4), pp. 53-58.

Oda, K., Takano, T., Doihara, T. and Shibasaki, R. (2004). Automatic building extraction and 3D city modeling from LiDAR data based on Hough transformation. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 35 (B3), pp. 277-280.

Pu, S. and Vosselman, G (2006). Automatic extraction of building features from terrestrial laser scanning. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(5), pp. 25-27.

Rutzinger, M., Elberink, S. J. O., Pu, S. and Vosselman, G. (2009). Automatic extraction of vertical walls from mobile and airborne laser scanning data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 38 (W8), pp. 7-11.

Vosselman, G. (2009). Advanced point cloud processing, Proc. Photogrammetric Week, Stuttgart, 7-11 September, pp. 137-146.