ACTIVE CONTOUR MODEL FOR AUTOMATIC BUILDING EXTRACTION WITH AERIAL LIDAR DATA- CASE STUDY IN PART OF COLOMBO, SRI LANKA

Lakmini Somawansha(1), Hina Pande(2), Poonam S. Tiwari(2)
[1]Survey Department of Sri Lanka
[2]Indian Institute of Remote Sensing, Indian Space Research Organization, Dehradun.
Email: lakminisomawansha@gmail.com

KEY WORDS:

Rule based classification, Elevation threshold, Transformation model, Snake model

ABSTRACT

Automatic extraction of buildings in urban scenes using geospatial techniques has become a subject of growing interest, particularly with the emergence of LiDAR systems since mid-1990. Recent developments in the field of remote sensing have introduced new sensor technologies in usage of LiDAR, SAR, and high-resolution optical data. Classification performance is expected to increase through combining these various data sources. 3D geoinformation plays a major role in generating useful information which could be used towards a variety of application fields e.g. architecture, urban and transport planning, surveying and mobile telecommunications. 3D models have become increasingly important in the field of city and regional management (tourism, telematics, civil protection, real estate management, and financial management).

The purpose of this study is to develop an approach for automatic extraction of buildings in urbanized and suburbanized areas using very high spatial resolution multispectral aerial images and LiDAR data set. The methodology focuses on improved building boundary polygonization from high resolution range and intensity data. The Active Contour (Snake) model is initialized and augmented by integrating with LiDAR data. Enhancement of building boundary polygonization is attempted by combined use of high resolution optical image and high density LiDAR point cloud. A rule-based procedure was employed to combine intensity and range information to automatically delineate building boundaries with 3D information. Broad zones of cultural sites were also done. Qualitative and quantitative measures are used for evaluating the performance of the proposed method.

INTRODUCTION

Automatic building extraction from satellite imagery in urban and residential scenes has become a subject of growing interest in the domain of remote sensing. Automatic extractions of multi-sensor data are very important for now a day. It is useful to various areas like as mapping and updating maps, land use land cover mapping, disaster management building reconstruction, urban planning, change detection, telecommunication and many other socio-economic activities. Remote sensing and GIS techniques play a vital role in such applications. In fact, possessed by complementary multi-sensor data such as Light Detection And Ranging (LiDAR) and optical imagery is specific to automatic extraction of building. Building extraction using the automatic techniques has a great potential and importance.

In a LiDAR system pulses of light travel to the ground. When the pulse of light bounces off its target and returns to the sensor, it gives the range (a variable distance) to the Earth. Hence, how this system earned its name of Light Detection and Ranging ((GISgeogrphy, 2016)).

There are three primary components of a LiDAR instrument the scanner, laser and GPS receiver. Other elements that play a vital role in the data collection and analysis are the photo detector and optics. LiDAR systems are divided into following types based on its platform- those are Space borne Airborne

LiDAR & Terrestrial LiDAR. Airborne LiDAR is installed on a helicopter or drone for collecting data. Airborne LiDAR is divided into two types. Topological LiDAR and bathymetric LiDAR. Topographic LIDAR typically uses a near-infrared laser to map the land, while bathymetric LiDAR uses water-penetrating green light to also measure seafloor and riverbed elevations. Terrestrial LiDAR systems are installed on moving vehicles or tripods on the earth surface for collecting accurate data points. Terrestrial LiDAR systems have two types. Those are Mobile LiDAR and Static LiDAR.

Remote sensing technology is a major component for the monitoring of physical and biological processes, identifying environmental attributes and measuring other parameters. The remotely sensed data or information identifies the geographic location on Earth and its boundaries such as natural or constructed features, oceans and more. A systematic study of aerial and space images usually involves several basic characteristics of features shown on an image, namely, colour, tone, texture, pattern, size, and shape, which help in the recognition or interpretation of various features on the enhanced satellite imagery during the classification of features. A digital orthoimage may be created from several photographs mosaicked to form the final image. The source imagery may be black-and-white, natural colour, or colour infrared with a pixel resolution of 1-meter or finer. With orthoimagery, the resolution refers to the distance on the ground represented by each pixel.

The images are represented as MxN matrix arrays. A pixel is referred by its column, row and band number. The different levels of image processing include low-level, mid-level and high-level process. The low-level process includes noise removal and image sharpening, the mid-level process includes object recognition and image segmentation and high-level process includes automatic navigation and scene understanding.

High-resolution images and LiDAR data have shown to improve the building extraction results effectively rather than using data from single sources alone. Automatically extracted and refined field boundaries cannot be used directly as a GIS input because it is not correct boundaries. So an active contour or snake model can be used to refine the 'actual' boundaries. Snakes were originally introduced way back in 1988 as a mid-level algorithm which combines geometric and/or topologic constraints with the extraction of low-level features from images. The active contour model, or snake, is defined as an energy minimizing spline – the snake's energy depends on its shape and location within the image. A smooth 2D curve which matches to image data, Initialized near target, iteratively refined and restore missing data. They are often used in computer vision and image analysis to detect and locate objects, and to describe their shape. An active contour is an ordered collection of n points in the image plane.

LITERATURE REVIEWS

A large number of automatic extractions of building techniques have been reported over the last few decades, particularly with the emergence of LiDAR systems. The 3D reconstruction of building comprises two important steps an improvement involving the fusion of high resolution aerial imagery with a LIDAR DSM was latter proposed (Clode, 2004).The detection step is a classification task and delivers regions of interest in the form of 2D lines or positions of the building boundary. The reconstruction step constructs the 3D models within the regions of interest using the available information from the sensor data. The detection step significantly reduces the search space for the reconstruction step (Khoshelham a. e., 2005) applied a split-and-merge technique on a DSM guided image segmentation technique for automatic extraction of roof planes. In evaluation, the accuracy of reconstructed planes was shown for four simple gable roofs only. Reconstructed buildings with straight (flat and gable roofs only) and curvilinear (flat roof only) boundaries from LIDAR and image data. Though the evaluation results were promising, the method could not detect buildings smaller than $30m^2$ in area and for the detected buildings both planimetric and height errors were high. After that in 2006 (Park, 2012) large complex buildings reconstructed using LIDAR data and digital maps. This method was able to reconstruct buildings as small as $4m^2$. However, in the absence of a ground plan, or if the plan is not up to date, the method becomes semi-automatic.

The prominent data driven methods for 3D roof reconstruction is presented For instance, (Rotten B. S., 2003) proposed a building detection method exploiting primarily LiDAR data while removing vegetation using imagery data. (Gunho Sohn, 2007) focused on exploiting the synergy of IKONOS multispectral imagery combined with a hierarchical segmentation of a LiDAR digital elevation model (DEM) to extract buildings. Another method of building detection was proposed by (Mehdi Ravanbakhsh, 2010) based on building masks obtained from LiDAR and multispectral imagery. These methods using both complementary sources, namely LiDAR data and optical imagery, achieve better building extraction results. Other building detection and extraction methods utilize only LiDAR data such as (Khoshelham e. a., 2005). They involve segmentation algorithms and classification using attributes such as building size, shape, height and Principal Component Analysis features. However, these approaches usually face problem of misclassification of vegetation as buildings.

Over the years, existing works in the domain of aerial or satellite imagery and airborne LiDAR fusion have addressed very specific acquisition contexts, where the respective image and LiDAR 3D point cloud are already registered and/or they are acquired from the same platform at identical or very close dates. Solutions proposed in the 2013 GRSS Data Fusion Contest focused on performing a fusion between LiDAR data and hyper spectral imagery with the same spatial resolution and acquisition dates on two consecutive days. In 2015, the contest involved extremely high resolution LiDAR data and RGB imagery collected from the same airplane with the sensors rigidly fixed to the same platform. Thus, the solutions submitted to these contests have never been intended to overcome the inherent obstacles of datasets collected from different platforms with different acquisition configuration at different moments and even in different seasons, with different spatial resolutions and levels of detail. The need for a relevant registration in such context is exemplified in the work undertaken by Curaetal.

STUDY AREA AND MATERIALS

In this study, the study area is located at Colombo divisional secretariat area situated in Colombo district, Sri Lanka it is shown figure number 1. It has one of the largest artificial harbors in the world and handles the majority of Sri Lanka's foreign trade. The city offers historical monuments, colonial architecture, beaches, and fine dining and shopping. Its architecture has been influenced by Portuguese, Dutch, and British colonization. The British influence is clearly visible in the buildings located in the Fort, an area where the larger business houses and the stock exchange are situated.

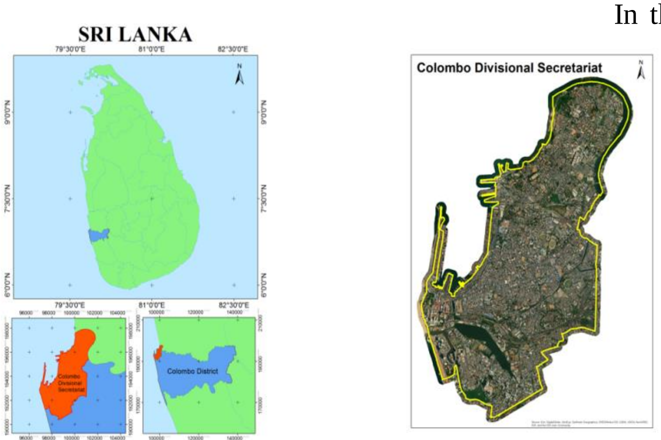

Figure 1 Study area

Dataset

In 2014-2016, Japan government introduced Airborne LiDAR (IR - Near Infra-Red laser) technology and provided technical cooperation to the department of survey by implementing a project aimed at creating a Digital Elevation Model (DEM) to enhance the disaster resiliency of Sri Lanka. LIDAR data are very important for this study. Using LIDAR data easy to remove same color different elevation levels (e.g. Road & roof top). Dataset details shown table number 1.

Table 1 Dataset

LiDAR data	Aerial image
Spatial resolution/Point density - 3Points/m²	Spatial resolution – 0.5m
Vertical accuracy ±30m	Spectral resolution – R, G, B
Acquisition time - 2016-09-26	Acquisition time – 2016-09-26

METHODOLOGY

The methodology adopted in this project is to extract a building from LiDAR data and high-resolution satellite images using automatic extraction technology. Those steps are represented figure number 2. The two major phases included in the procedure are: Elevation threshold, Rule based classification.

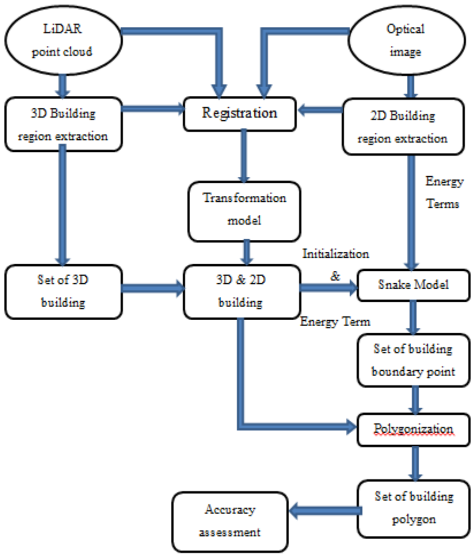

Figure 2 Flow chart

Registration

In this study LiDAR data and aerial image captured same platform, same date. Both are dependently each other. It is automatically registered data. LiDAR data and aerial image not registration each other, such a context yield spatial discrepancies between data sets that provide the active contour model with wrong initial points. Therefore, a registration has been down firstly. This registration is very important and its accuracy is effect of each and every step.

Building region extraction

In here each and every step very important. Vertical projection is given to one value for important features to study and other non-important features give to zero value. After this step only visible to important features. Morphological operators input image must be binary. In a morphological operation, each pixel in the image is adjusted based on the value of other pixels in its neighborhood. Morphological operators are four types.

1. Dilation 2.Erosion 3.Opening 4.Closing

Dilation operation makes an object to grow by size. The extent to which it grows depends on the nature and shape of the structuring element.

Erosion operation is complement of the dilation operation in context with the operation effect. That is erosion operation causes object to lose its size

Opening operation is of an image is a combinational operation of erosion and dilation.

The closing of an image is also a combinational operation of erosion and dilation. It differs from the opening operation in the sense of order of occurrence of erosion and dilation operation.

After this step all point merge together. Remove small region is very small point not merges each other, remove that point.

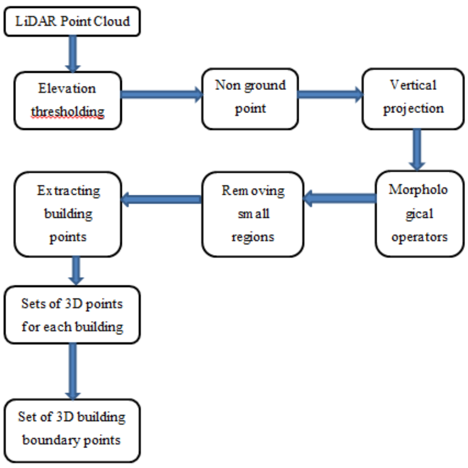

Figure 3 Building region extraction from LiDAR Point Cloud

Using LiDAR Point Cloud

Figure number 3 shown elevation threshold method using LIDAR data. For each LIDAR point, the corresponding DEM height is used as the ground height (Hg). An elevation threshold Eh = Hg +2 .5m (Rotten B. S., 2003)is then applied to the raw LIDAR elevation. The LIDAR data are divided into two groups: ground points such as ground, road furniture, cars and bushes which are below the threshold, and non-ground points which represent elevated objects such as buildings and trees. (Xu, 1997)

Using High Resolution Optical Image

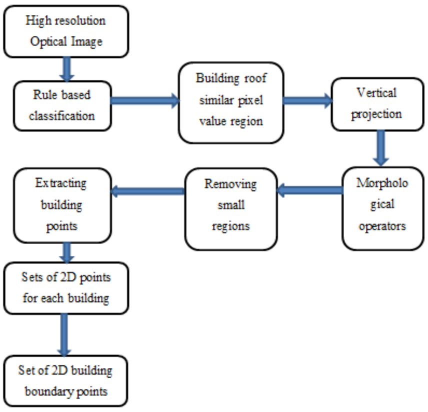

Figure 4 Building region extraction from High Resolution Optical Image

Figure number 4 shown in rule based classification method using high resolution areal image. In this method used high resolution aerial data and satellite data. Give training data for Each and every subset individually. Pixel values are different to each other. So can't use same training data sample to every subset. In this accuracy depend on given training samples quantity. Give to more than six training data samples in each class it accuracy is high.

Transformation Model

Using LiDAR point cloud method it only removes given elevation threshold below point. It includes building and tree point. Using high Resolution Optical Image method it includes building roof pixel value similar all points.

After running this model only building area come to 1 values and other area come to 0 values. This model is multiplication model. Both image included features come 1 value and others gone to 0.

Snake model

$$E_{snake} = \int_0^1 (Eint(x(s)) + Eext(x(s)))ds$$

Equation 3 Energy function

$$E_{int}(x(s)) = ½\alpha|x'(s)|2 + \beta|x''(s)|2$$

Equation 1 Internal Energy Function

$$E_{ext}(x(s)) = E_{img}(x(s)) + E_{con}(x(s))$$

Equation 2 External Energy Function

An active contour, or a snake is a dynamic curve x(s) = (x(s), y(s)), where s ∈ [0,1] is the normalized arc length, defined within an image domain that is deformable under the influence of internal and external forces (Xu, Prince, 1997). Mathematically, the behaviors of the snake are governed by an energy function, Where E_{int} and E_{ext}, respectively, represent the internal and external energy terms. The internal energy relates to the tension (the amount of stretch) and the rigidity (the amount of curvature) of the snake, respectively controlled by weighting parametersαandβ. x'(s) and x''(s) denote the first and second derivatives of x(s) with respect to s. The external energy E_{ext} is composed of the forces due to the image itself E_{img}, and other constraint forces introduced by the users Econ, e.g. inflation force introduced by balloon model (L.D., 1991).

RESULT AND DISCUSSION

Extracted Building Region Using Elevation Threshold Model from LIDAR Point Cloud

In figure number 5 represented automatic extracted building region using elevation threshold model from LIDAR point cloud. This is very important part in this study. Different features have same pixel value (e.g. road and building roof). Using ruled base method difficult properly classify this features. So this step is very important to my study.

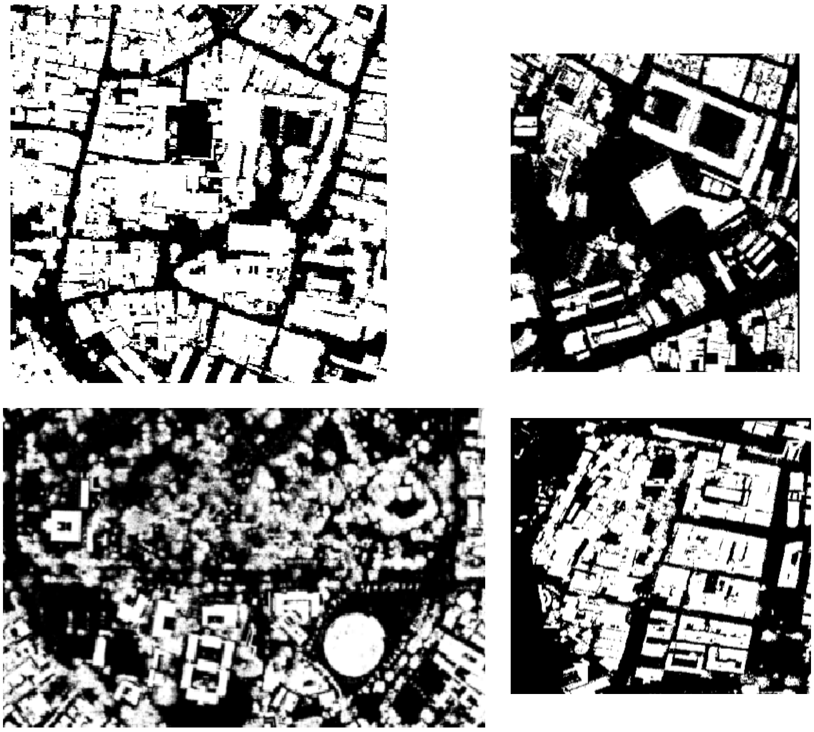

Figure 5 Extracted building region using elevation threshold model from IDAR point cloud

Extracted Building Using Rule Based Classification from High Resolution Optical Data

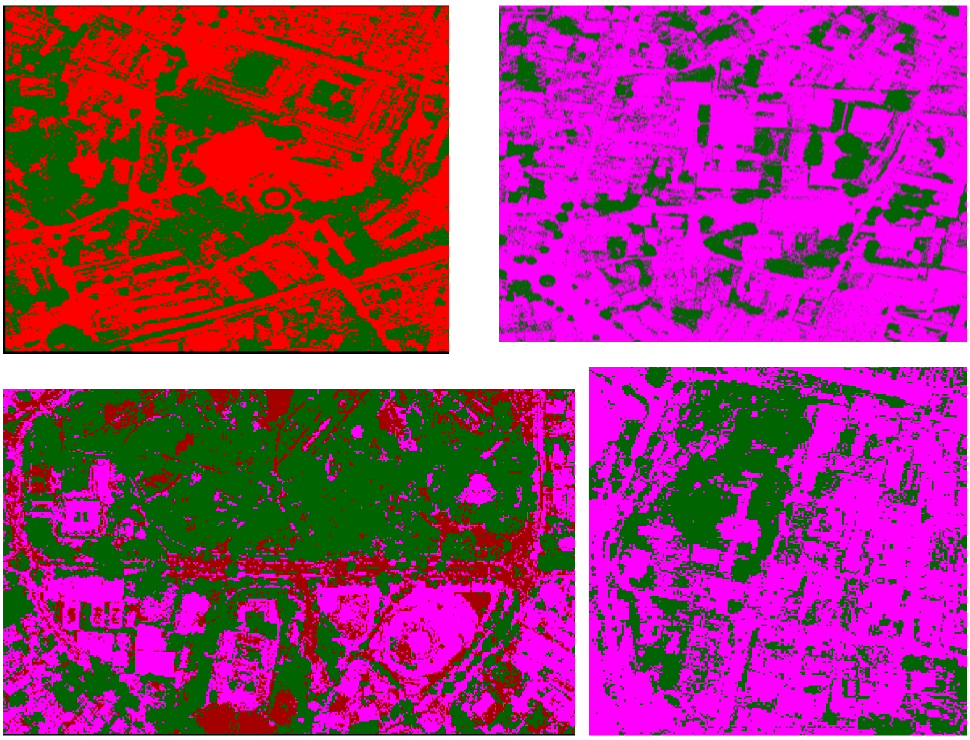

Figure 6 Extracted building using rule based classification from high resolution optical image

In this study not only use LiDAR point cloud, also used high resolution optical images. Different features have same elevation (e.g. trees and buildings). Using elevation threshold method can't classify only building. So this study used rule based classification method in figure number 6 represented that. This method accuracy depend on quantity and quality of given training data.

Automatic Extracted Building Using Transformation Model from LIDAR Point Cloud and High Resolution Optical Data

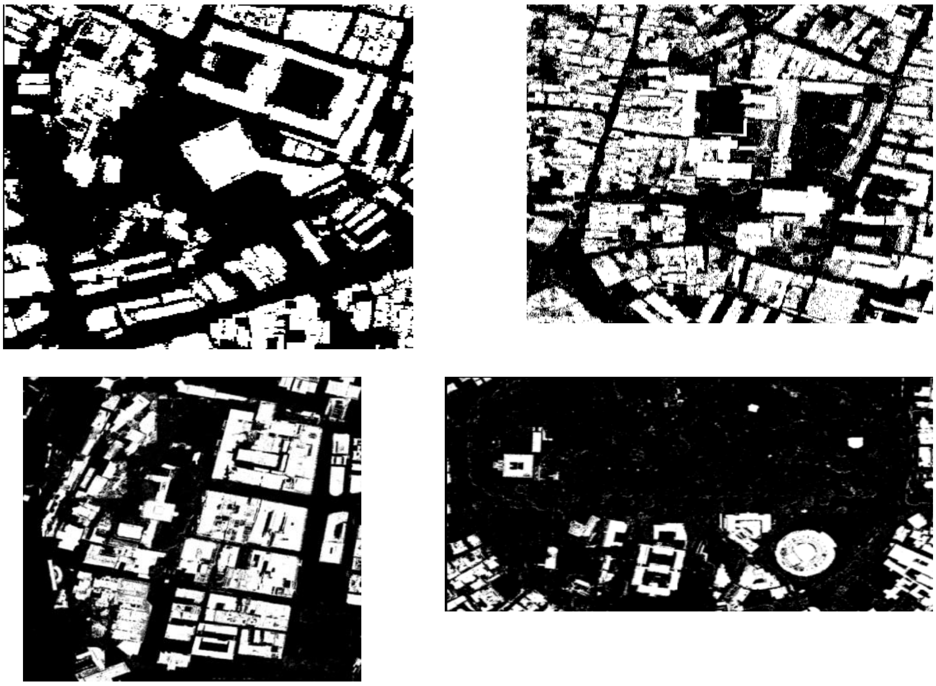

Figure 7 Automatic extracted building using transformation model from LIDAR point cloud and high resolution optical image

In figure number 7 represented automatic extracted building using transformation model from LIDAR point cloud and high resolution optical image. In this study before steps individually used LiDAR point cloud and high resolution optical image. This step used for merging that both data. In this study develop this model and no need big knowledge to programming. It is very useful and easy model.

Automatic Extracted Building after Doing Morphological Operations

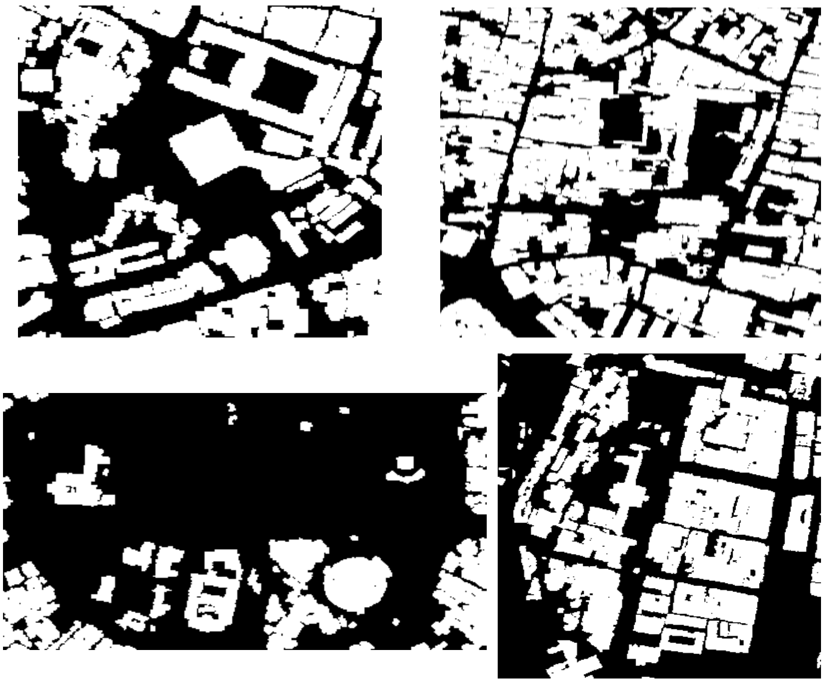

Figure 8 Extracted building after doing morphological operations

In figure number 8 represented automatic extracted building after morphological operations. Each and every automatic extraction study used morphological operations. In this study used morphological operations is to remove the imperfections in the structure of image.

Building Segmentation with Active Contour Model

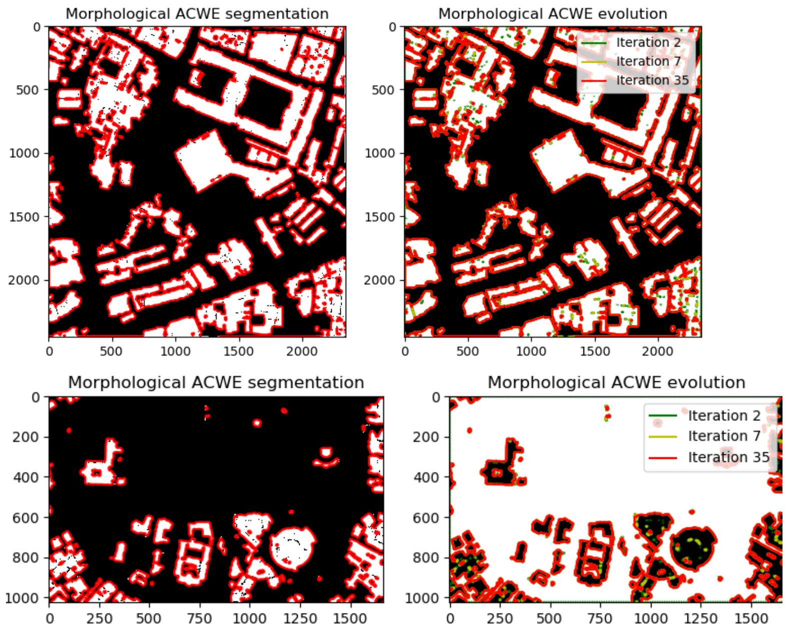

Figure 9 Building segmentation with active contour model

Practically this method is strongly depends on parameter α which controls the propagation of moving curve. If α value is large, we cannot control the curve and if α is small then curve cannot evolve efficiently and results in poor segmentation. If region to be segmented has clearly defined boundary, then moderate value of α gives better segmentation.

ACCURACY ASSESMENT

In table number 2 represented final accuracy in this research. The accuracy assessments for building extraction are intended to compare the results of different algorithms, rather than to evaluate the extraction and the matching results in an absolute way. Because these results are additionally quite different and still relatively far away from a perfect solution, a simplified set of measures is justified.
The definitions of the quality measures are presented in the following. (Christian Wiedemann, 1998)

1. Completeness
2. Correctness
3. Quality

Completeness

$$Completeness = \frac{Area\ of\ matched\ reference}{Area\ of\ reference}$$

Equation 4 Completeness

The completeness is the percentage of the reference data which is explained by the extracted data, i.e., the percentage of the reference network which lie within the buffer around the extracted data.
The optimum value for the completeness is 1.

Correctness

$$Correctness = \frac{Area\ of\ matched\ extraction}{Area\ of\ extraction}$$

Equation 5 Correctness

The correctness represents the percentage of correctly extracted road data, i.e., the percentage of the extracted data which lie within the buffer around the reference network.
The optimum value for the correctness is 1.

Quality

$$Quality = \frac{Area\ of\ matched\ extraction}{Area\ of\ extraction + Area\ of\ unmatched\ extraction}$$

Equation 6 Quality

The optimum value for the quality is 1.

Table 2 Accuracy assessment

	Subset 1	Subset 2	Subset 3	Subset 4
completeness				
Accuracy	0.90	0.88	1.00	0.98
Percentage	89.66%	88.47%	99.90%	98.12%
Correctness				
Accuracy	0.98	1.00	0.93	0.99
Percentage	97.85%	99.67%	93.48%	98.58%
Quality				
Accuracy	0.96	0.99	0.88	0.97
Percentage	95.63%	99.34%	87.76%	97.19%

CONCLUSION

This report has presented a new method for automatic building extraction through effective integration of LIDAR data and aerial orthoimage. Like any existing methods, the proposed building extraction method uses a number of algorithmic parameters, the majority of which are either adopted from the existing literature or directly related to the input data.

The proposed method is fully automatic and experimental results show that it not only offers high reconstruction rates but also can work in the presence of moderate registration error between the LIDAR data and orthoimage. However, as the registration error grows, so does the likelihood that algorithm will fail to properly extract the buildings, especially the small portion.

REFERENCE

Christian Wiedemann, C. H. (1998). Empirical evalatin of automativally extracted road axes. 172-187.

Clode, S. R. (2004). The Automatic Extraction of roads from LIDAR Data. *JAPRSIS*.

GISgeogrphy. (2016, March 09). *A Look at Elevation Models in GIS*. Retrieved March 05, 2020, from DEM, DSM & DTM Differences: http://gisgeography.com/dem-dsm-dtm-differences

Gunho Sohn, I. (2007). Data fusion of high resolution satellite imagery and LiDAR data for automatic building extraction. *ISPRS Journal of Photogrammetry and Remote Sensing*.

Khoshelham, a. e. (2005). A split-and-merge technique for automatedreconstruction of roof planes. *Photogrammetric engineering and Remote Sensing*.

Khoshelham, e. a. (2005). A split and merge technique for automated reconstruction of roof planes. *Photogrammetric engineering and Remote sensing*.

L.D., C. (1991). On active contour models and ballons. *CVGIP: Image understanding*, *53*, 211-218.

Mehdi Ravanbakhsh, M. A. (2010). Building detection from multispectral imagery and LiDAR data employing a threshold-free evaluation system. *Saint-Mande: Cooperative Reaserch Centre for Spation Information, The University of Melboune*.

Park, a. e. (2012). Diversity of morphology and function in arbuscular mycorrhizal symbioses in Brachpodium distachyon. *Planta*.

Rotten, B. S. (2003). *Automatic generation of building models from LiDAR data and the integration of aerial images.* Vienna: Leibniz Universitat Hannover.

Rotten, B. S. (2003). *Automatic generation of building models from LIDAR data and the integration of aerial images.* Vienna: Leibniz Universitat Hannover.

Xu, C. P. (1997). Gradient vector flow: A new external force for snakes. Computer Vision and Pattern Recognition. *IEEE* (pp. 66-71). 1997IEEE Computr Society Conference on IEEE.