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AUTOMATIC EXTRACTION OF PLANAR OBJECTS FROM LiDAR POINT CLOUD DATA

PhD Thesis

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Supervisor

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THESIS APPROVAL

This thesis entitled “**Automatic Extraction of Planar Objects from LiDAR Point Cloud Data**” was prepared by **Abu KAMARA** under the supervision of **Assoc. Prof. Dr Sedat DOĞAN** has been accepted with unanimously votes by our jury as A Thesis Submitted to the Institute of Graduate Studies in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in the result of thesis defence exam conducted on June 25, 2021.

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DECLARATION

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DECLARATION OF THESIS ORIGINALITY REPORT

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ÖZET

LiDAR NOKTA BULUTU VERİLERİNDEN DÜZLEM NESNELERİN OTOMATİK OLARAK ÇIKARILMASI
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Harita Mühendisliği Ana Bilim Dalı
Doktora, Haziran 2021
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Nokta bulutu verilerinden tam veya yarı-otomatik olarak nesnelerin çıkarılması problemi, çok büyük miktardaki veri ve problemin karmaşıklığı nedeniyle oldukça zor bir iştir. Bu tezde, düzlemsel nesnelerin LiDAR nokta bulutu verilerinden çıkarılması amacıyla model-tabanlı yöntemler, RANSAC ve en küçük kareler yöntemiyle düzlem uydurma optimizasyon tekniği ile yorumlanmıştır. RANSAC (Random Sample Consensus) algoritması, rasgele seçilen örneklerin iteratif hesaplar sonucunda model ile uzlaştırılması yaklaşımı olarak tanımlanabilir. Bu yaklaşım iyi bilinen ve yorumlanması kolay bir yaklaşım olmasına rağmen, problemin karmaşık yapısı ve büyük verinin analiz edilmesi zorunluluğu nedeniyle doğru sonuçların elde edilmesi ve elde edilen düzlem parçalarının anlamlı nesneler oluşturacak şekilde gruplandırılması işi, çözümü oldukça zor olan bir problemdir.

Bölümleme (segmentation) modelleri 2- boyutlu bir görüntüdeki nesnelerin dış sınırlarını tam olarak bulabilmektedir. Bunun için sınıflandırma (classification) modellerinin tersine, bir nesnenin piksel piksel tanımını yapmaktadır. 3- boyutlu nokta bulutu verilerinde ise, sınıflandırma yapılabilmekte ve ancak nesne adaylarının sınırlandırıcı kübü (bounding box) elde edilebilmektedir. Bu küp içerisindeki aday nesnenin analitik tanımı, optimizasyon sonucunda elde edilen düzlem parametreleriyle yapılmıştır.

Anahtar Sözcükler: RANSAC, Nokta Bulutu, Düzlem Çıkarma, Bölümleme, Sınıflandırma, LiDAR, Otomatik, Yapay nesneler, Yüzey

ABSTRACT

AUTOMATIC EXTRACTION OF PLANAR OBJECTS FROM LiDAR POINT CLOUD DATA
Abu KAMARA
Ondokuz Mayıs University
Institute of Graduate Studies
Department of Geomatics Engineering
PhD, June 2021
Supervisor: Assoc. Prof. Dr. Sedat DOĞAN

Full or highly automated object extraction from point cloud data is a challenging task due to the huge amount of data and the complexity of the problem. In this thesis, we obtained the Model-based methods for planar objects extraction from LiDAR point cloud data by using the Random Sample Consensus (RANSAC) algorithm together with automatic least-squares plane fitting optimization. Although the RANSAC model is known well and easy to implement, obtaining correct results is too difficult because of the complexity of the huge data and obtaining correct partitioning of the fitted planes into meaningful objects. A new paradigm, Random Sample Consensus (RANSAC), for fitting a model to experimental data is introduced. RANSAC is capable of interpreting/ smoothing data containing a significant percentage of gross errors and is thus ideally suited for applications in automated image analysis where interpretation is based on the data provided by error-prone feature detectors.

Segmentation models provide the exact outline of the object within an image. That is, pixel by pixel details are provided for a given object, as opposed to Classification models, where the model identifies what is in an image, and detection models, which place a bounding box around specific objects. The objective of segmentation on point clouds is to spatially group points with similar properties into homogeneous regions. Segmentation is a fundamental issue in processing point clouds data acquired by LiDAR and the quality of segmentation largely determines the success of information retrieval.

The proposed method demonstrates that the RANSAC algorithm and the segmentation approach are robust even in the presence of many outliers and a high degree of noise.

Keywords: RANSAC, Point Cloud, Plane Extraction, Segmentation, Classification, LiDAR, Automatic, Artificial structures, Surface.

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From them, I have gotten a love of knowledge and the desire to work hard to achieve one’s goals.

My last and final thanks go to all those whose names I didn’t mention, you all in diverse ways made me the man I am today and I am forever grateful.

Abu KAMARA

DEDICATION

This thesis is dedicated to the memory of my loved ones that have passed away I miss you all every day, I love you all but Allah love's you most.

Finally, this thesis is dedicated to all those who believe in the richness of learning.

TABLE OF CONTENTS

ABBREVIATIONS AND ACRONYMS

LiDAR	Light Detection and Ranging (LDR)
RANSAC	Random Sampling and Consencious
3D	Three Dimension
2D	Two Dimension
BIN	A method of grouping the data into segment
kNNs	k nearest neighbours (kNNs)
CS	Consensus Set
MSS	Maximum Sample Set
DEM	Digital Elevation Model
LAS	File format designed for the interchange and archiving of lidar point cloud data
LAZ	Popular for publishing LiDAR data because LAZ files are usually many times smaller than LAS files
DTM	Digital Terrain Model
SFM	Structure From Motion
MVS	Multi-View Stereo
HT	Hough Transform
CCL	Connected Component Labeling
OT	OcTree
MSAC	M-estimator SAmple Consensus
Points	The coordinate of points in the decomposition.
PointBins	Indices of the bin that each point belongs to.
BinCount	The total number of bins created.
BinBoundaries	BinCount-by-6 [MIN MAX] coordinates of bin edges.
BinDepths	The # of subdivisions to reach each bin.
BinParents	Indices of the bin that each bin belongs to.
Properties	Name/Val pairs used for creation)
EO	Exterior Orientation
Location	Matrix of [X, Y, Z] point coordinates (read-only)
Colour	Matrix of point RGB colours
Normal	Matrix of [NX, NY, NZ] point normal directions
Intensity	Matrix of point grayscale intensities
Count	Number of points (read-only)
XLimits	The range of coordinates along the X-axis (read-only)
YLimits	The range of coordinates along the Y-axis (read-only)
ZLimits	The range of coordinates along the Z-axis (read-only)

LIST OF FIGURES

LIST OF TABLES

1. GENERAL INTRODUCTION

1.1. Introduction

3D coordinates of objects and obtained results are the dense point clouds that are directly measured by the airborne laser scanners or LiDAR (Pu & Vosselman, 2009). During the laser scanning of point clouds including terrain, vegetation, buildings, and many more recordings are made that belong to the terrain and off-terrain object (Hao, Dadbakhsh, Seaman, & Felstead, 2009). The commonly used technique in the extraction of Digital Terrain Model (DTM) generation, change detection application and 3D building modelling is the LiDAR point clouds (Yastikli & Cetin, 2016). DEM generation application, building extraction, LiDAR data processing, the LiDAR point classification is the first step in all the later. Building based on the LiDAR data properties and LiDAR point is classified into meaningful partitions such as building vegetation and ground that is the first step in LiDAR point classification. The result of the classification is directly used in the application because accurate classification is crucial to achieving accurate building extraction, 3D city models and many more (Charaniya, Manduchi, & Lodha, 2004).

Irregular distributed raw LiDAR point cloud data or regularly distributed is the required technique used in LiDAR point classification. Because of the potential use of the image processing methods, the most preferred data structure is the gridded LiDAR (Clode, Kootsookos, & Rottensteiner, 2004). The disadvantages of using the gridded LiDAR data depends especially on characteristics point loss on buildings, losing height accuracy, and vegetation (Antonarakis, Richards, & Brasington, 2008). Most of the proposed classification algorithm is focus on the classification of the irregular distributed raw LiDAR point cloud data to eliminate losing height accuracy and characteristics point loss. In the classification stage, using LiDAR point cloud data properties such as scan angle, intensity elevations, multi-returns, and many more, each 3D irregular distributed point cloud is assigned to a semantic object class in the raw LiDAR data classification. (Niemeyer, Rottensteiner, & Soergel, 2014) there is a high need task of automation classification because if it is done manually the process is time-consuming and costly. (Moussa & El-Sheimy, 2010). Nowadays, the research on the classification of the LiDAR point cloud is targetting mainly to develop an effective technique for the said approach to avoid time-consuming. (Forlani, Nardinocchi, Scaioni, & Zingaretti, 2006)

Organised planning of modern cities is considered to be very important in the life of a human as a major development. To improve the qualities and management of urban areas there is a need for the current spatial data. Therefore how data are obtained plays a very crucial part in urban development and planning. Buildings extraction that is automatic plays a very useful role for most applications such as infrastructures of various project planning, mobility population analysis, surveillance to get rid of illegal infrastructure in metropolitan areas. The approach is very necessary for an urban area that is closer to natural disaster regions so that they are easily traced and rescue. (Uzar & Yastikli, 2013)

In recent years, there has been a huge number of equipment that process 3D points clouds. Major examples are LiDAR, the multi-view stereo (MVS) algorithm and many more. The disorganised points are referred to as a 3D coordinate list. Many factors undermine the process to be an outlier. Points come from surfaces that are list expected to be extracted from. Due to such most results in many algorithms can be heavily corrupted (Lovreglio et al., 2010)

LiDAR has become very instrumental especially in 3D city modelling and topographic mapping which is a direct method for collecting huge accurate 3D LiDAR point clouds. Much progress has been reported that 3D city modelling is a strong focus on the reconstruction of a 3D building (Yan, Jiang, & Shan, 2012). Of all the studies, it has been assumed that the reconstruction of a building is a polyhedra model that consists of a primitive plane. Reconstruction of building roof can be decomposed into two steps that are topology construction and 3D roof facets. The 3D roof facets detection of a building depends and quality mainly on its accuracy (Elberink & Vosselman, 2011)

Clustering, classification, and segmentation are the basic methods and techniques that involves generally in obtaining 3D roof facets. (Sampath, 2010). To detect planes from the building roof a local surface normal is used to calculate the neighbourhood 3D point cloud. Noise is a huge challenge in calculating the surface normal. Because of challenges in the measurement of the surface normal, a huge amount of LiDAR data is obtained during the scanning process in which a large portion is a noise. If a huge amount of neighbourhood data is selected from the unstructured LiDAR it leads to an accuracy challenge in calculating the surface normal (Yan et al., 2012).

In this thesis, our contribution is semi or using an automatic means to obtain a plane from LiDAR point clouds using Matlab code, Random Sampling Consensus (RANSAC) algorithm is robust in obtaining planes from the LiDAR point clouds. To obtain a plane, a minimum of three points were selected in the LiDAR point clouds. We selected the normals of nearest neighbours with components n_x, n_y, n_z in the LiDAR point clouds to obtain a plane. The LiDAR point clouds were iterated and planes that were reasonable enough (close to reality) were identified as inliers and the LiDAR point clouds that were not close to reality in obtaining the plane were identified as outliers. The consecutive creation of 3D models of objects measure and the LiDAR point clouds is still a topic of research. There were challenges because the LiDAR point cloud is huge, we obtained segmentation of the LiDAR point clouds to process and classify the LiDAR point clouds of the points that partition them into various segments; properties of the same points shows that they belong to the same partition. The plane obtained was a group of LiDAR point clouds that fit into a similar segment. Based on the results in the experimental section of this thesis, recognition is equivalent to the segmentation of the obtained planes in LiDAR point clouds since the obtained planes are closed to reality. The LiDAR point cloud used in this thesis is classified as LAS.

1.2. Aim of the Research and Methodology

1.2.1. Aim

This thesis aims to utilize the RANSAC algorithm in obtaining Automatic Extraction of Planar Objects from LiDAR Point Cloud Data using the Model-based methods. The Model-based methods have purely mathematical principles (Zeileis, Hothorn, & Hornik, 2008). Though the Model-based method is robust and fast to points that are not similar to reality, the method limitation is that dealing with the accuracy of huge LiDAR point clouds from different sources. The main aim of our method is to group the LiDAR point clouds that have the same mathematical relationship into one segment. The robust model that is used to detect mathematical features like circles, spheres, lines, and many more is RANSAC (Bolles & Fischler, 1981). The Model-based method is suitable for model fitting and it is now the state of the earth. In the present day, many subsequent works have inherited the Method-based method in obtaining 3D LiDAR point cloud segmentation. Because of the complex geometry of the LiDAR point cloud data, it was observed that RANSAC find the wrong plane that has little or no information of the obtained image. Due to such a challenge in our RANSAC algorithm, we obtained the Segmentation and Classification approach. The target of Segmentation and Classification was to accurately place the LiDAR point clouds into multiple homogeneous partitions. A very active field of research that is gaining much interest is point classification (Grilli, Menna, & Remondino, 2017). The quick acquisition in Automatic Extraction of Planar Objects from LiDAR Point Cloud Data is a key task for the majority of surveying fields.

1.2.2. Methodology

In this thesis, LiDAR point clouds are segmented into multiple homogeneous partitions. The partitioning of the LiDAR point clouds distribution is such that points fall into a partition that has the same properties of $x, y, and\ z$. We had a challenge in the inspection of points that has a similar property to the local point partitioning of LiDAR point clouds segmentation and searching for normals of nearest neighbour points with the components n_x, n_y, n_z based on the idea that each point required an inspection. Due to the huge amount of LiDAR point clouds, the iteration process takes a long period that was the main purpose of partitioning the LiDAR point clouds into the segments.

LiDAR point clouds obtained from the surveying to extract the Planar Objects from LiDAR Point Cloud Data in this thesis work is huge. The point partitioning of a similar LiDAR point cloud is most time unorganized and after segmentation, points that partition the tendency of falling into neighbouring sub-group is high. Each point partition represents a particular object surface. The possibility that an object surface represents more than one group of a point is high or an obtained partition contains more than one object surface. Based on that fact, we obtained segmentation since points are randomly partitioned by considering neighbouring points to extract the targeted plane rather than a consensus sample (CS). We observed that our approach was efficient in dealing with huge LiDAR point clouds since we had a challenge in the RANSAC algorithm.

For irregularly partitioned points, grouping neighbouring points is usually achieved by repeatedly finding the k nearest neighbours ($kNNs$) of each point (Sankaranarayanan et al., 2007). For image processing, a connected component labelling (CCL) algorithm is often used for grouping connected pixels (Barrasa, González, & Martínez, 1992), while the algorithm can also be revised and applied on 3D grids (Lohmann, 1998). A similar study of grouping neighboring points is that (Esme, Bucksch, & Beekman, 2009), which used the adjacency of octree nodes to build a graph of botanic trees for terrestrial LiDAR point clouds.

(M. Wang & Tseng, 2010) proposed an octree-based split-and-merge algorithm for the reliable segmentation of coplanar points. Split-and-merge segmentation, which refers to a kind of region segmentation algorithm, is frequently used for image segmentation (Tiwari & Rekapalli, 2020; M. Wang & Tseng, 2004). When the algorithm is applied to a LiDAR point cloud, a point cloud is iteratively split into groups of coplanar points, and split point groups are organized into an octree structure. The neighbouring coplanar point groups are then merged to complete the segmentation.

1.2.3. Extraction of Plane

In 3D LiDAR point clouds plane extraction many researchers have put forward different algorithms. The Model-based method using an algorithm of Random Sampling Consensus (RANSAC) (Schnabel, Wahl, & Klein, 2007) has widely been obtained. RANSAC algorithm is highly robust with outliers the approach uses an iterative means to obtain inliers that correspond to the extracted plane. Because the RANSAC algorithm takes a bit longer to obtain a model plane with huge data many variants of approach were implemented (Hillerkuss et al., 2011). (Meng et al., 2016) obtained connected component analysis and performed the Hough transformation on the first-cloud point then RANSAC algorithm approach to "surfels" (2s per 640 x 480 points) refine resulting of each and pre-segment.

In this thesis, to extract planes Segmentation and Classification was obtained to partition the LiDAR point clouds into clusters. We obtained a Matlab Las reader to constructs Las / Laz file reader object, a Las reader, that can read in LiDAR data from ASPRS. Since the distance of the LiDAR point from the plane obtained are normal to the plane we used the plane equation. Orthogonal to the plane is the shortest distance to the plane. Equation (1.1) below determine a vector and a point in 3D coordinate space that is perpendicular to the extracted plane.

$$ax + by + cz = d \qquad \textbf{(1.1)}$$

where at least one of the numbers that represent a,b, and c must be non-zero. A plane in 3D coordinate space is determined by a point and a vector that is perpendicular to the plane.

Iteration, in the context of computer programming, is a process wherein a set of instructions or structures are repeatedly iterated in a sequence that a specified number of times until a condition is met. The iteration value for the plane segmentation filter has a large impact on the processing time. As the number of iteration changes the number of internal iteration to attempt to find a match, increasing the number only serves to increase the chance of finding a better match. So as long as the number is above a minimum value, the result should be more or less the same. Due to the number of iterations, we considered the plane that has the best inliers. In this thesis, points that form a plane are perpendicular because if parallel there will be no result for plane formation. We did a test of three points selection to know whether they are parallel using two vectors. If the two vectors prove to be parallel, it means that the plane can not be formed in such a situation. Since the result was needed, we continued with the iteration process until arrived at a point that is good to go with an inlier reasonable enough.

The original RANSAC algorithm is used to describe the best model in a given set of LiDAR point clouds. The best model obtained from the algorithm is the parameter. In this thesis, obtained points in MATLAB were considered to be the best plane that fit the huge set of points. The distance of the point to the plane is within the distance threshold because point lying to the plane is significantly distant from each other. This challenge can be handle by deleting the final list of points from the raw data set of LiDAR points cloud and filter then save. This makes a lot of sense that add value as another input to program implementation. Doing the latter, target distance is selected and use that indicate the best distance from the plane to the point selected.

Obtaining the best planes within the given LiDAR point clouds RANSAC algorithm is used in the extraction process that iterates till a reasonable plane is obtained in Matlab software. Determining all the best planes, the first step is that an introduction plane must be within a user-specific distance and the highest point on the initial plane is checked. If there is no link at the first instance, the iteration process continues with the aim that the introduced plane is the highest targeted point. The target is to investigate whether the distance point falls within, if the target is obtained then there will be a joining point to the initial plane set of the two processed planes. The condition of the program is not limited to two planes that connect each other rather multiple of the homogeneous plane as long as they fulfilled the same characteristics properties.

Traditionally, RANSAC Algorithm is an optimization technique that was first introduced by (Bolles & Fischler, 1981). This Algorithm is used to determine the exact model for a given data set. The data set may be contaminated by certain parameters, for example, incorrect data due to noise. Such data that does not give correct information or possess contaminated information is considered as outliers. Applying the RANSAC algorithm, 50% of unorganized points were removed from our data set. The unorganized points are referred to as outliers.

RANdom Sample And Consensus (RANSAC) is a robust algorithm estimator wherein two major steps are involved generally:

(1) Hypothesize (2) Test

Step 1: Hypothesize: This parameter is a model parameter which means considering Minimal sample sets (MSS). It can be done by a random selection of points.

Step 2: Test: In the case of the test, we consider the entire data set and compute with the result of step:1. In the end, RANSAC determines the data sets which is similar to the plane model parameter. We referred to the step as a Consensus Set (CS). The two steps, Hypothesize and Test are done iteratively until a certain threshold reach suitable enough.

RANSAC obtain only one plane at a time and in that respect, the iteration is repeated until a reasonable plane is obtained from the point cloud. RANSAC algorithm that defines a plane is term as classical RANSAC which applies to the plane model. 3 points are randomly selected that define the plane p . The data will be iterated and after the iteration, the plane that has the best good to go we term that plane as “inliers”. In our work, we selected the nearest neighbours considering their n_x, n_y, n_z normal components. We divided the data into partitions to ease our process since the data is too huge for the machine to operate.

Geometric primitive shape uses the model-based in the grouping of points. A segment in this thesis referred to points that have the same mathematical representation. RANSAC algorithm is a well-known algorithm that was introduced by M. Fischer, 1981. The mathematical features like a circle, straight line and many more are detected by a robust model known as RANSAC. The RANSAC algorithm is now the state-of-the-earth that fit plane. Nowadays, the segmentation of 3D point clouds has been inherited by subsequent work.

1.2.4. K- means Clustering

In this present day, point clouds and 3D models are the most popular being that they are currently used in many fields, some of the data are collected through mobile phones and later transferred to the internet. Besides all these broad availabilities, it is still considered that there is more room for improvement in terms of research rather than the state-of-the-art, preferably automatic extraction of artificial primitive structures, to provide 3D data with meaningful attributes that characterize and provide significance to the objects represented in 3D. Generally, Segmentation is the process of grouping point clouds into multiple homogeneous regions with similar properties whereas classification is the step that labels these regions. In this thesis, our main interest in K – means clustering is to analyze the clusters and algorithms with the motive of segmenting and classifying 3D point clouds.

In this section, the algorithm provides a simple but efficient implementation of K-means clustering. We grouped n-dimensional points into K-means clustering such that points fall into groups which it is closest to. Considered n_x, n_y, and n_z. In such a situation, vector implies that K-means (X, K) partitions the points in the N-by-P data matrix X into K clusters. This partition minimizes the sum, over all clusters, of the within-cluster sums of point-to-cluster-centroid distances. Rows of X correspond to points, columns correspond to variables. Note: when X is a vector, KMEANS treats it as an N-by-1 data matrix, regardless of its orientation. K-MEANS returns N-by-1 vector indices containing the cluster indices of each point. By default, KMEANS uses squared Euclidean distances. The parent cluster (raw data in the form of las) is most times referred to as seeds wherein the random selection of uniform clusters obtained in this thesis work each with the probability proportional from it a distance of the remaining points. With k-means, a two-phase iterative algorithm is obtained in this thesis to minimize the sum of point-to-centroid distances, summed over all K clusters.

The first phase uses what the literature often describes as "batch" updates, where each iteration consists of reassigning points to their nearest cluster centroid, all at once, followed by recalculation of cluster centroids. This phase occasionally (especially for small data sets) does not converge to a solution that is a local minimum, i.e., a partition of the data where moving any single point to a different cluster increases the total sum of distances. Thus, the batch phase is thought of as providing a fast but potentially only approximate solution as a starting point for the second phase. The second phase uses what the literature often describes as "online" updates, where points are individually reassigned if doing so will reduce the sum of distances, and cluster centroids are recomputed after each reassignment. Each iteration during this second phase consists of one pass through all the points. The online phase will converge to a local minimum, although there may be other local minima with a lower total sum of distances. The problem of finding the global minimum can only be solved in general by an exhaustive (or clever, or lucky) choice of starting points, but using several replicates with random starting points typically results in a solution that is a global minimum.

Traditionally, an unsupervised learning algorithm is simply referred to as K-means clustering that is only used with data that is unloaded like groups or without categories. The major aim of the approach is to find a segment in data that represent the K variable. Based on the characteristics or properties in the data group segmentation will be obtained. Clustering is done based strictly on their similarities. We obtained a data set of the point cloud, with clusters, and values of these clusters (XYZ coordinate). The huge task is to categorize the clusters into groups. To acquire our interest, we use the K-means algorithm. This means work because we considered clusters as points in an n-dimensional shape. The algorithm categorizes the k group into groups of similarities. To measure those similarities, we used the Euclidean distance as a measurement. The following are the way the k- means algorithm in this thesis work;

- First, we initialize k points, called means, randomly.
- We categorize each cluster to its closest mean and we update the mean’s coordinates, which are the averages of the clusters categorized in that mean so far.
- We repeat the process for a given number of iterations and in the end, we had our clusters.

The “points” mentioned above are called means because they hold the mean values of the clusters categorized in them. Using parameters of some algorithms in the iteration process, steps of segmentation, and classification in which the means were obtained.

Using k- means, the fitted planes look a lot better. But to further improve the results, an outlier detection method needs to be used to eliminate some of the outliers which could be skewing the plane. With k-means clustering, RANSAC becomes a lot closer to reality (Rather than a vertical plane). RANSAC is very helpful in preventing points from skewing the fitted plane. All the outliers disregard when fitting the plane, they could be part of some underlying fault structure. The outliers later are studied to understand the complex structure of the fault. Traditionally, clusters fall into regions wherein they have the same z-values.

1.3. Least Squares

The classic least-squares regression fits a line to data where errors may occur only in the dependent variable, while the independent variable is assumed to have no errors. The total least squares regression fits a line where errors may occur in both variables. A least-squares method is a form of mathematical regression analysis that finds the line of best fit for a dataset, providing a visual demonstration of the relationship between the data points. Each point of data is representative of the relationship between a known independent variable and an unknown dependent variable. We considered the segmentation of 3D point clouds as paramount. The main challenge of the above method is its irregularities of point clouds from different sources. We compute the point of intersection of the two lines of the corresponding sides to determine the coordinates of the corner of the rectangle.

Generally, the least-squares method provides the overall rationale for the placement of the line of best fit among the data points being studied. The most common application of this method, which is sometimes referred to as "linear" or "ordinary", aims to create a straight line that minimizes the sum of the squares of the errors that are generated by the results of the associated equations, such as the squared residuals resulting from differences in the observed value, and the value anticipated, based on that model.

2. STATE-OF-THE-ART

2.1. Edge Based Method

The quantity of data to be processed reduces significantly using the edge based-method, however, the essential information that tells much about the shape of the object is left prominent. The information explains in the edge-based about an image is accepted by an object of a huge quantity that is obtained in a computer version and many more. The method is advantageous in edge line that has a suitable orientation and the edge detection lecture which has been present during the last three decades. To judge the performance directory there is no required technique for edge detection technique to be performed. Separately and personally the performance is been evaluated based on its application.

Segmentation of image edge-based detection is mostly needed. The method transforms the image of the original form into an edge image that has lots of benefits like grey tones changing into an image. Computer version processing of an image, detection of edge treats very important variations of an image that has a grey level, their physical detection and objection of the geometric characteristic of the object of the scene. Fundamentally it detects, outline object and boundaries amount the object and also the image background. With significant breakdowns in values, intensity edge detection is highly prominent.

The intensity in an image, edges are local. Between two regions edges occur. Features of high importance are obtained from edges. This method has a prominent feature that analyzes an image. The computer version algorithm uses this method in an advanced form. This method is used in object detection that serves various application purposes. The method is still open to research. Discontinues are mainly three types in grey level which are edges, line and point. To detect all three types of image discontinues the spatial masks is used. (Muthukrishnan & Radha, 2011).

Though segmentation in the edge-based method obtains at a faster rate there are challenges with density with an uneven distribution in point clouds and also very noise sensitive.

2.1.1. Region-Based Method

To obtain differences between different regions, LiDAR point clouds obtain the approach of region-based points that has the same neighbourhood characteristics of nearby points to extract the isolated region. In terms of comparison, the accuracy of region-based is better in the area of noise than that of edge-based. The challenge of the method is under segmentation or over-segmentation and accuracy in obtaining border regions. In this thesis work, the method is divided into a two-step, unseeded region(top-down) and seeded region (bottom-top).

The segmentation process in the seeded region start with selecting points that have several seed points, within the selected points, each seeded region will multiply themselves provided they satisfied the same conditions. This algorithm was first proposed by (Besl & Jain, 1988). The algorithm is further breakdown into two: Curvature identification of each seeded point and then based on the criteria that predefine the grown region such as point proximity and surface planarity. The challenge of this approach is that it is time-consuming and noise sensitive. Many proposals have been done to upgrade this method. (Koster, Lei, Anderson, Martin, & Bryant, 2000) submitted an approach that crate pyramid graph of the irregular version to save various data between regions. To merge adjacent regions and compare we use this information. In this work (Rusu, Marton, Blodow, Dolha, & Beetz, 2008), in describing smoothness, use the approach of the seeded region as in (Rabbani, Van Den Heuvel, & Vosselman, 2006). In (Tóvári & Pfeifer, 2005) airborne laser data is used to introduce a region growing approach. The distance to the growing plane and the normal vector was proposed by this method for growing the seed points.

(Krogan et al., 2006) the region seed growing algorithm is adapted to the planar surface (Vosselman, Gorte, Sithole, & Rabbani, 2004) in TLS data segmentation. To recognize potential building features, point clouds that have vital properties were retrieved from the segments. (Ning, Zhang, Wang, & Jaeger, 2009) introduced an approach that includes two stages as detail segmentation and rough. The issue of rough is to obtain the main object from a scene based consensus set in a plane that has the same normal vector. To obtain finer data for object components, segmentation has to be done in detail that refined the process. (Dorninger & Nothegger, 2007) a sequential implementation of the clustering algorithm was obtained by reducing the complexity of the time. Information on coarse contour and hierarchical clustering segment the original points in this method.

The approaches in this method depend highly on the seed point that has been selected. Inaccuracy is of great importance because it leads to over-segmentation and under-segmentation. Selection and controlling causes a huge amount of time in the growing process. Thresholds compatibility depend on chosen segmentation result. There is another huge challenge on the issue of increasing points because points increase locally that is sensitive to noise.

The top-down approach is known as the unseeded region. Grouping points into regions is stepped one. The process is breakdown into smaller regions by subdivision. The process continues if the selected regions of the subdivision have similar properties. (Chen & Chen, 2008) obtained this approach to guide the process to complete the geometry of architectural building to reconstruct and clustering planar region. Based on the confidence rate of the local area to a planar surface, the work introduces a segmentation method. There are some other challenges to this method which is that it can not perform well when segmenting objects such as trees and over-segmentation. The main challenge is how and where to subdivide the unseeded region. It also required a huge amount of prior knowledge that is unknown to complex scenes.

2.1.2. Attribute-Based Method

Based on the clustering of LiDAR point cloud the attribute-based is a robust approach. The attribute base has two steps. The computation approach is the first step, the second step, the point cloud is a cluster-based on competition of attributes. Flexibility is observed in the clustering approach to incorporate different cues into segmentation processes, attribute and accommodate the spatial relationship. The challenge of the approach is its dependability on high derived attributes. To produce the best separation among data the point cloud attribute clustering approach should be computed precisely.

(Biosca & Lerma, 2008) dealing with terrestrial laser point clouds in segmentation they implemented fuzzy algorithm and unsupervised clustering approach as a new strategy. The fuzzy algorithm adapts to the parameter of the method that is useful in the combination of the clustering merging method. Depending on the time-consuming and choosing the best parameter, the result of the method could be promising.

(Doytsher, Filin, & Ezra, 2001) for laser data clustering a methodology was put forward. Due to the approach, surface texture measure has no limitation requiring the data volume which is processed or surface texture in data defining the window identity. Without direct rasterization that operates on laser point, there is an adaptation on varying point density. A modern version of the method is found in S. (Filin & Pfeifer, 2006). With this method slope adaptive is obtain using the normal vector that is derived from the neighbourhood system. Using the attribute of points the neighbourhood among the measuring point is defined e.g., vertical point distribution or horizontal, density point and distance. In each direction slope of the normal vector, point differences and its closest points are considered as attribute clustering. Outliers influence can be eliminated in this method.

(Vosselman & Dijkman, 2001) uses a 3D version in a well known Hough transformation to segment planar surface in a laser point cloud. Each point can be redefined as a 3D attribute in this method. The author shows that the method is instrumental in successfully obtaining planar faces from the irregularly distributed point clouds that sometimes result in noise that can cause over-segmentation.

To group points into the homogeneous region, the most robust approach method is attribute-based. Accuracy and flexibility are the targets of this method. Definition of point density in points clouds and neighbourhood between points are the specific areas that the method relies upon. The other challenge of the method is time-consuming when a huge amount of multidimensional attributes of the input point cloud.

2.1.3. Model-Based Methods

To group points, the Model-Based methods obtain geometric primitive shapes like sphere, cone, plane, cylinder and many more. Partitioning of points into segments are done with points that have the same mathematical properties. (Fischer & Lynch, 1981) proposed the RANSAC (Random Sampling Consensus) algorithm that is well known. The most robust method the extract mathematical features circle, straight lines and many more is the RANSAC. The model-based is now the-state-of – earth. Many studies have been done recently in the field of 3D LiDAR point clouds that have to obtain this algorithm.

(Schnabel et al., 2007) segmenting point cloud data and mesh the RANSAC algorithm was implemented. The approach is to use automatic means to detect an unorganized point cloud that has a basic shape, obtain an optimization speed step while the accuracy of the result is still maintained. Even amid a huge amount of noise, the method is robust to outliers. The challenge of the model-based is that of calibration in terms of input size of point cloud and shape size within the data.

Gelfand et al. submitted broaden primitive shapes limitation (Mitra, Gelfand, Pottmann, & Guibas, 2004)a sippable shape approach to be detected. Rotationally and traditionally symmetrical is known as sippable shapes that includes many features. The idea is been obtain to segment data of point cloud of complex structures shape by mear margin sippable surface initial. Initial patches are hard to determine due to such accuracy depend on such.

(Tarsha-Kurdi, Landes, & Grussenmeyer, 2007) the detection of roof plane automatically from point cloud laser data are compared both in Hough transform and RANSAC. Besides, the challenge faced by the algorithm is still in the position of been the most appropriate in terms of running time and segmentation. It can process a large amount of input data in negligible time. The slower and most highly sensitive noise in segmentation based on parameter values is the 3D Hough transform.

(Sievers et al., 2011) an algorithm was implemented to globally consolidate the obtained result in the RANSAC method. For local fitting of a primitive plane, RANSAC is used. Primitive obtained in local RANSAC stage is been corrected by global primitive and brings it to a reasonable size. Segmenting point clouds the technique can be obtained to refine the parameters of the fitted primitive.

Purely mathematical principles embedded in the model-based method. The method is highly effective in dealing with outliers. Dealing with huge point clouds from different sources the method face challenges.

The algorithm is mainly based on interactiveness for parameter extraction from an observed data set. Classically RANSAC can be defined as follows;

1) Randomly select 3 points from data, which will define a plane p.

2) Find the distances of the remaining points from the plane p. The points with a distance smaller than a critical distance t are called "inliers" and belong to plane p. Record the three points and the number of inliers, this record is called “best_model”.

3) Repeat the process of 1) and 2) *k* times or until no planes with point numbers bigger than *d* can be found. In each time, if the number of inliers is greater than those

in the *best_model*, replace the *best_model* maintained earlier with the new one. In the end, the parameters of the plane model are determined from the final *best_model*.

As above, it's clear that RANSAC can only estimate one plane for a particular data set. To detect all planes, the RANSAC algorithm is repeated until no more planes can be found. At each time, points that belong to a plane will be excluded from the original data.

In the context of data-driven approaches that provide more universal models, the automatic detection of planes is a crucial operation.

2.1.4 Graph-Based Methods

Point clouds are considered in graph format in this method. Neighbourhood points are connected to certain pairs and they are vertex that corresponds to each point in a data that is known as the simple model. Due to the efficiency of the method that gains popularity in the robotic application, it is clear that the graph-based is highly accurate. FH algorithm is an approach that is well-known (Felzenszwalb & Huttenlocher, 2004). The algorithm operates like Kruskal's algorithm that finds a minimal spanning tree in a graph it is efficient and simple.

(Golovinskiy, Kim, & Funkhouser, 2009) (KNN) nearest neighbours of k is used in point cloud to build a 3D graph. There is an implementation of a penalty function for smooth segmentation to be encourage wherein the background is poorly connected to the foreground that will minimize it with min-cut. The approach of this method is fully automatic or a user interface is been interacted with that needed prior knowledge of segmented object to its location.

Segmenting coloured 3D laser points cloud, the method of graph-based has been expanded by (Strom, Richardson, & Olson, 2010), Strom et al. The work presented based on the union a segmenting criterion of colour and surface normal that is defined by co-registered sensors. Segmentation of colour point clouds can successfully be done for both outdoor sensors and indoor sensors. It is shown in this experiment that it can be run in real-time that is more robust than the colour image alone or segmenting laser data alone. The challenge of the method is that the results of segmentation are noise sensitive to colour information and has a very complex system that is needed. The limitation of this method is it requires a complex sensors system and the segmentation results are sensitive to colour information.

This work of this method has been cited in many publications such as Conditional Random Fields (CRF) (Lafferty, McCallum, & Pereira, 2001). (Rusu, Blodow, & Beetz, 2009) geometric surface primitive with different points labelling this method has been proposed using CRF. Like (Nurunnabi, Belton, & West, 2012) The method is based on segmenting surfaces, feature descriptor extractor termed as Fast Point Feature Histograms (FPFH) (Rusu et al., 2009) to surround the local surface point. Even in midst of heavy noise the method segment 3D points based on their surfaces successfully through 3D geometric surfaces classes definition and use of contextual information with CRF.

(Q. Wang, Schoenberg, & Jackson, 2010) implemented another version of the algorithm to segment 3D dense points cloud that generated data range from a fusion of a single optical camera and a laser scanner. Markov Random Field (Thrun et al., 2006) uses the method to correspond to each pixel image by estimating a 3D point. With this method, textured huge point clouds are generated from sparely interpolating range laser finder data that are constrained by an alignment optical image. The graph weights are headed as Euclidean distance combination differences in pixel intensity and each estimated angle between normal surfaces. Successfully the method segment complex urban environment point cloud with performances of near real time.

Compared to other methods the graph-based method performs better in terms of results even amid uneven diversity and heavy noise. The most unique challenge of the method is that in real-time the method can usually not run. Camera system and special required co-registration or training steps offline may sometimes be needed.

2.2. Hough Transformation

A more reliable and efficient approach was introduced in 1962 by Paul Hough to detect binary lines in images (Hough, 1962). To obtain better parameter space cluster features, Paul's introduced an idea that was highly built upon transforming spatial extended patterns. Paul's idea brought forward to hold on to the challenge of global image space detection to a simple local peak detection in the area of parameter space.

Hough Transformation methods ideas highlighted various advantages as mention in the lines. The issue of real-time application, edges were treated independently to process points parallelly that suitable enough. Next, the issue of partly deformed and noise shape based on its scheme selection. Finally, since each cell has a specific parameter space in cell multiple, occurrences of lines can be detected by HT because each occurrence is quite specific.

In (Bhattacharya, Liu, Rosenfeld, & Thompson, 2000), for blocks, boxes and 3D lines there is a devised detector. Parallel line space that uses a 2D Hough detection line, the computational cost of the method was reduced. Planar face extraction uses the 3D Hough transformation as an approach to obtain point clouds that are irregularly distributed.

(Tarsha-Kurdi et al., 2007) presented the technique of the airborne laser scanner to obtain 3D models as a highly appropriate means. The artificial structure extraction is proceed depending on the viability of the 3D LiDAR data. Hough Transformation is one of the most instrumental approaches in 3D plane extraction. The experimental aspect of this thesis shows the comparison of both RANSAC and that of the Hough Transformation algorithm which demonstrates sensitivity and processing time to the distribution of points within the 3D. Based on performances when compared RANSAC to that of HT, the algorithm of RANSAC is fast and efficient whilst that of HT is segmentation parameter sensitive in values. The challenge of the RANSAC algorithm is that at times construction of 3D is generated that in reality, they do not exist.

In recent decades there have been lots of attractions of the HT in terms of research. The major's advantage of the HT algorithm is that it is robust to occlusion, noise immunity and transform expandability. Variation of many from HT has evolved which covered shape detection from lines to that of irregular shape in terms of a spectrum. There is still an expectation that appearances of new variation will soon be available that would bring more recognition of complex objects. Binary images at most times change and applied their varients. At present days, many applications have made use of the Hough Transformation in numerous fields of life and there is room for more unconventional ones shortly.

2.2.1. Fuzzy Classification Methods

Training information and classification results are represented in a one-pixel-one class method in the conventional remote sensing supervised classification. The class mixture cannot be taken into consideration while training a classifier and also in determining pixels membership. The limitation has reduced the classification accuracy level and leading to poor extraction of information. This limitation can be reduced by adopting the fuzzy classification technique.

In a fuzzy supervised classification technique, geographical information can be represented as fuzzy sets. The algorithm consists of two major steps vis-à-vis the estimate of fuzzy parameters from fuzzy training data, and a fuzzy partition of spectral space. Partial membership of pixels allows mixed cover classes within a pixel to be identified and more accurate statistical parameters to be generated. This, in turn, allows for a higher classification accuracy to be achieved.

The fuzzy set theory provides useful concepts and tools to deal with imprecise information. Partial membership allows that the information about more complex situations, such as mixed cover or intermediate conditions, can be better represented and utilized. However, works in remote sensing image analysis using fuzzy sets are rather scarce (Cao & Wang, 1990). (Tumer & Ghosh, 1996) developed a fuzzy knowledge-based approach for classifying sub-pixel land cover. This approach emulated the expert’s knowledge base and the heuristics in the framework of fuzzy set theory.

(Jeansoulin, Fontaine, & Frei, 1981) Proposed to measure properties of image entities in terms of several criteria and use the tools of fuzzy set theory to combine the criteria for automating multitemporal segmentation. (Dinarello et al., 1986) developed a fuzzy c-means clustering algorithm to perform unsupervised classification for a Landsat TM image. In the algorithm, fuzzy sets have been mainly used to represent intermediate results. (Di Zenzo, Bernstein, Degloria, & Kolsky, 1987) developed a fuzzy relaxation algorithm for contextual classification. Where cover classes have been regarded as fuzzy sets. Set-theoretic operations have been used to adjust membership grades of pixels to classes. (Kent & Mardia, 1988) used a fuzzy membership model to perform classification on Landsat data. However, their statistical parameters have been generated from ground truth recorded as a hard membership process (Cao & Wang, 1990).

Advantages of fuzzy supervised classification when compared with the conventional methods, is that this method improves remote sensing image classification in the aspects of:

- Representation of geographical information,
- Partitioning of spectral space and,
- The estimate of classification parameters.

❖ Identification of cover class components of mixed pixels and higher overall classification accuracy can be obtained by using fuzzy classification. (Cao & Wang, 1990).

The limitation is that if the techniques of fuzzy set theory are mainly employed in limited, usually intermediate, phases of the works, it will inevitably lead to the loss of valuable information that could otherwise be used to obtain better results. (Cao & Wang, 1990)

Accuracy assessment or validation is an important step in the processing of remote sensing data. It determines the value of resulting data to a particular user i.e., the information value (Janssen & Vanderwel, 1994).

The measures of classification accuracy derived from the confusion matrix are inappropriate for the evaluation of fuzzy classifications. There is, therefore, a need to derive measures of classification accuracy, which go beyond the confusion matrix (Gopal & Woodcock, 1994).

3. THE PROPOSED METHODS

To overcome some of the challenges mentioned above, we obtained Octree since it is an algorithm that partitions multiple homogeneous points into a segment. With Octree 3D points clouds are partition into the segment. There is a recursive breakdown of child partitions each into eight (8). Using Octree segments are divided into an equal subdivision with a portion having similar properties. The challenge is that with huge points there is a slower subdivision of weight to that of the same subdivision, with minimal subdivision decompositional is higher (Heimann et al., 2007). The model-based method is one in which the minimum x, y, z and maximum x, y, z are selected. RANSAC algorithm is a suitable approach that we used to obtain extracted plane since the Model-based method uses geometric primitives (Fischer & Lynch, 1981). Iteration was done by reassigned points to their nearest clusters centroid. It is the recalculation of the cluster centroid. Individual reassigning of points is done to avoid long-distance selection of points. RANSAC makes lots of sense because the unskewed data becomes closer to reality.

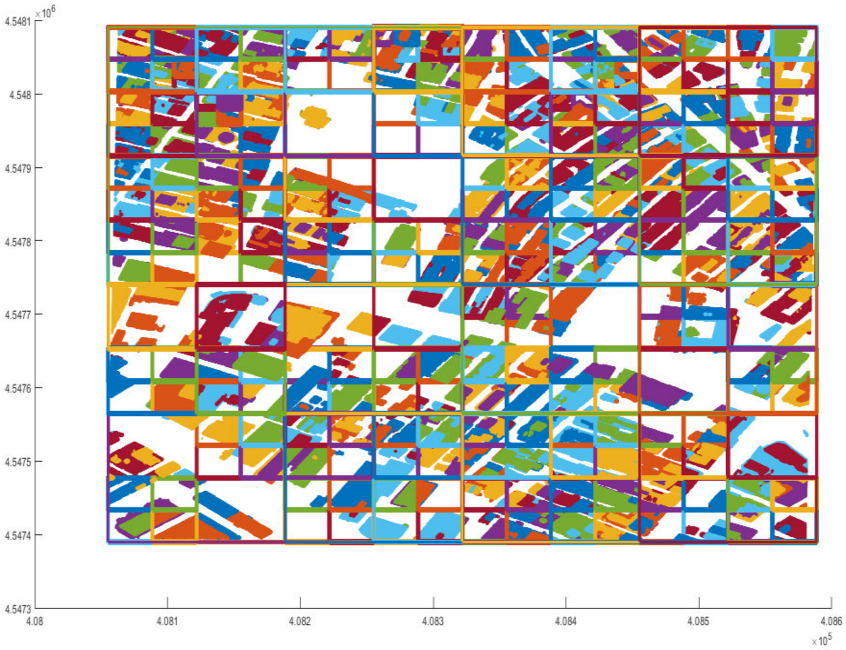

Figure 3.1. LiDAR point cloud OcTree Segmentation of the study area in Matlab

However, the parameter of iteration can go to infinity as long as it is needed. It is easy to extract geometric primitive shapes using Model-Based Methods (Andrews, Jin, & Séquin, 2012). In this thesis, we calculated for every point in other to find the normal in Matlab. To create a data structure of partition an octree is used. Portions are breakdown into segments of eight (8).

How categorical data or numerical distribution are made in their respective representation is known as ‘histogram’. The implementation was done first by (Norton, 1978). Range of values is the first step in histogram representation which means that to divide the whole range of values into several intervals and check the values that fall into each interval. Partitions are categorized into consecutive and an interval of non-overlapping variables. The bins are usually specified as consecutive, non-overlapping intervals of a variable. Interval is often of equal size and must be adjacent.

To obtain the robustness and efficiency of the proposed algorithm in this thesis work the datasets was shown in an octree that was later posted in the histogram. (Rabbani et al., 2006) compared terrestrial laser scanner (TLS) to airborne LiDAR datasets to obtain the history of point density. We remark that all the histograms in this thesis work were implemented to check the performance of our algorithm on the dataset densities. The histograms were formed by considering the points nearest neighbours. We aimed to only provide an insight into the input data but not a requirement for segmentation.

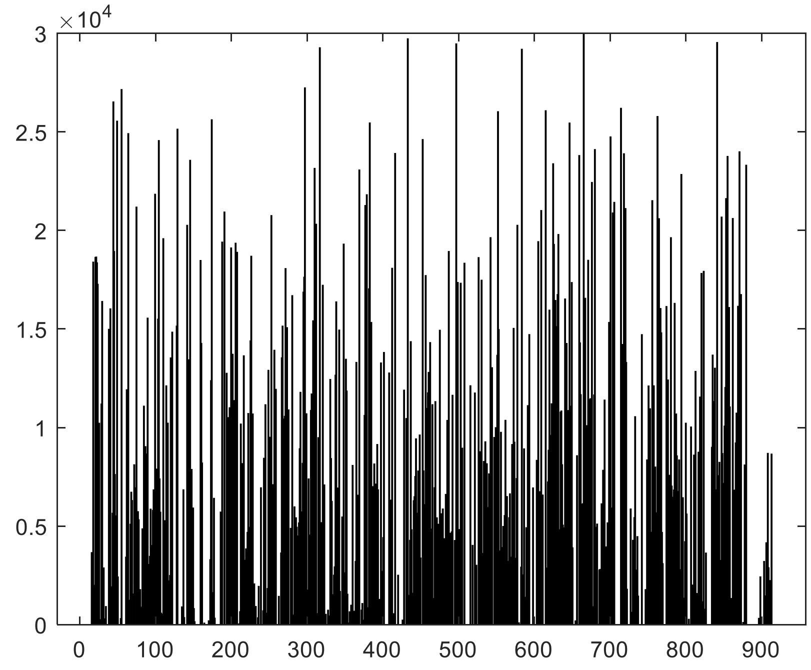

Figure 3.2. Matlab LiDAR point cloud data histogram of buildings in the study area

3.1. Mathematics of The Proposed Methods

In the first unit of this thesis work equation (1.1) plane extraction, we obtained a vector that is perpendicular to the plane and a point that expresses 3D coordinate space. We obtained the equation of the plane to solve the mathematics in Matlab. Nonzero normal vector $n = (a, b, c)$ through the point $X_0 = (x_0, y_0, z_0)$

$$\boldsymbol{n}.(\boldsymbol{X} - \boldsymbol{X_0}) = 0 \tag{3.1}$$

$$\boldsymbol{X} = (x, y, z)\ .$$

$$d = -ax_0 - by_0 - cz_0 \tag{3.2}$$

We explained the mathematics by obtaining n points in 3D and fit a plane to them. Decomposing a singular value on a matrix covariance to the obtained smallest eigenvalue of the eigenvectors. Generally, planes are described by normal vector equation (3.10) $\boldsymbol{n} = [a, b, c]^T$, distanced for point $\boldsymbol{p} = [x, y, z]^T$ on the plane $\boldsymbol{n}.\boldsymbol{p} + d = 0$. Planes are three–dimensional, however, equation (3.2) uses four values. In this thesis, we start by removing a component so that we can constrain the solution space. We arbitrarily assigned $c = 1$, visa vis, that z – component of the plane normal is always 1. One will think that our assumption is problematic.

$$ax + by + d = -z \tag{3.3}$$

$$\begin{bmatrix} x_0 & y_0 & 1 \\ x_1 & y_1 & 1 \\ x_n & y_n & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ d \end{bmatrix} = \begin{bmatrix} -z_0 \\ -z_1 \\ -z_n \end{bmatrix} \tag{3.4}$$

$$\begin{bmatrix} x_0 & x_1 & \cdots & x_n \\ y_0 & y_1 & \cdots & y_n \\ 1 & 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} x_0 & y_0 & 1 \\ x_1 & y_1 & 1 \\ x_n & y_n & 1 \end{bmatrix} \begin{bmatrix} a \\ b \\ d \end{bmatrix} = \begin{bmatrix} x_0 & x_1 & \cdots & x_n \\ y_0 & y_1 & \cdots & y_n \\ 1 & 1 & \cdots & 1 \end{bmatrix} \begin{bmatrix} -z_0 \\ -z_1 \\ -z_n \end{bmatrix} \tag{3.5}$$

$$\begin{bmatrix} \sum x_i x_i & \sum x_i y_i & \sum x_i \\ \sum y_i x_i & \sum y_i y_i & \sum y_i \\ \sum x_i & \sum y_i & N \end{bmatrix} \begin{bmatrix} a \\ b \\ d \end{bmatrix} = - \begin{bmatrix} \sum x_i z_i \\ \sum y_i z_i \\ \sum z_i \end{bmatrix} \tag{3.6}$$

$$\sum x , \sum y , \sum z = 0.$$

$$\begin{bmatrix} \sum x_i x_i & \sum x_i y_i & 0 \\ \sum y_i x_i & \sum y_i y_i & 0 \\ 0 & 0 & N \end{bmatrix} \begin{bmatrix} a \\ b \\ d \end{bmatrix} = - \begin{bmatrix} \sum x_i z_i \\ \sum y_i z_i \\ 0 \end{bmatrix} \tag{3.7}$$

$$D = \sum xx \times \sum yy - \sum xy \times \sum xy$$
$$a = (\sum yz \times \sum xy - \sum xz \times \sum yy)/D$$
$$b = (\sum xy \times \sum xz - \sum xx \times \sum yz\,)/D \qquad \textbf{(3.9)}$$
$$\boldsymbol{n} = [a, b, 1]^T$$

After calculation, we can conclude that $d = 0$, which means that we multiplied the last row $N.d = 0$. From mathematics most of the points are relative to the centroid of the point clouds, a plane passes through the origin. The plane is obtained based on the average input of LiDAR point clouds.

$$\begin{bmatrix} \sum x_i x_i & \sum x_i y_i \\ \sum y_i x_i & \sum y_i y_i \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = - \begin{bmatrix} \sum x_i z_i \\ \sum y_i z_i \end{bmatrix} \qquad \textbf{(3.8)}$$

$$D = \sum xx \times \sum yy - \sum xy \times \sum xy$$
$$a = (\sum yz \times \sum xy - \sum xz \times \sum yy)/D$$
$$b = (\sum xy \times \sum xz - \sum xx \times \sum yz\,)/D \qquad \textbf{(3.10)}$$
$$\boldsymbol{n} = [a, b, D]^T$$

We summarized that our z – component of the plane is non – zero. What if it does? It can show that our determinant calculation in equations (3.9) and (3.10) become zero or closer to zero which yields bad conditions and results in the plane extraction. What to do in such a case? One of the algorithms of the normal must be non-zero if the points do span the plane. This work minimizes huge errors, the squares of the remaining inliers as perpendicular to the main axis and not the remaining inliers perpendicular to the plane in Matlab. Obtained Octree segmentation, the remaining inliers of the LiDAR point merged with the resulting plane. We conclude that this work superseded the state – of — art.

3.1.1. Challenges of The Proposed Methods

In the last few years, segmentation has been the spotlight in the 3D LiDAR point cloud of which many significant types of research has been done. Segmenting point clouds in the real-time approach of many types have been brought forward to effectively deal with the process of segmentation. With this thesis work, however, the surface of the following application of robust real-time and the LiDAR point clouds has not yet been achieved due to many challenges.

Because of the large amount of LiDAR point clouds in this thesis work, segmentation of 3D LiDAR point cloud survey was extensively obtained. Step one was truly geometric reasoning techniques that mathematical models in which selected region or fitting model, to fit linear in the combination of robust estimator and LiDAR point cloud data to fit points to a nonlinear plane. The method in this thesis work was fast to run and the obtained result was reasonable. Our only challenge of the method is that choosing the size of the model in fitting the object is difficult, noise sensitive and won't work well when huge point clouds data are involved in Matlab. The second approach was how to obtain point cloud data using a 3D feature, uses our technique to analyze the different Planar Objects from LiDAR Point Cloud Data, and use the extracted structures to fit our model, Cloudcompare software.

Our technique compared to the - state – of – the – art outperform based on geometric reasoning and because point clouds take only a few minutes to run the iterated clusters in Matlab.

The integration of contextual information is one of the most important pieces many has been deviated from in the segmentation of 3D point cloud. (Nurunnabi et al., 2012) an obtained different view like a geometrical relationship, cues shape and many more in achieving good results We believed that our work supports contextual information that improves segmentation results with huge LiDAR point cloud data.

4. EXPERIMENT

The LiDAR point cloud data was obtained from İstanbul Turkey and the data belongs to “İstanbul city council municipality Test Project on Urban Classification”. In this thesis obtaining Planar Objects from LiDAR Point, Cloud Data is prominent. The raw LiDAR data is huge that consist of twelve million six hundred twenty – five thousand four hundred fifty – seven points (12,625,457). Huge LiDAR point clouds data has lots of challenges to handle. The data includes buildings of many types, roads, ground, and many more for Planar Objects from LiDAR Point Cloud Data. The airborne technique was used to obtain the data. Figure 4.1 shows the LiDAR points cloud data of the study area.

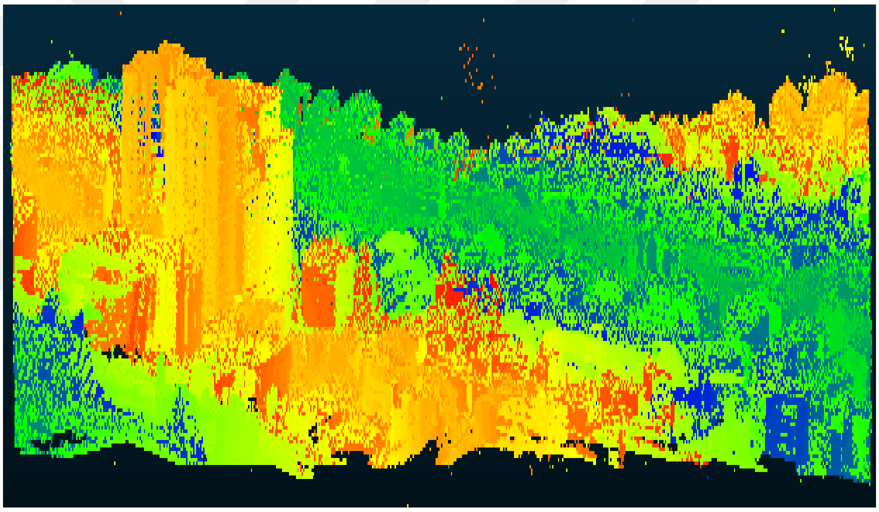

Figure 4.1. Study area in Istanbul

The Planar Objects from LiDAR Point Cloud Data with Segmentation and Classification has been obtained from the LiDAR point cloud of the study area. Due to the result of the extracted features, different types of buildings, roads, and the ground were obtained in Cloudcompare software. In this section, merge multiple LiDAR points cloud that segmentation and classification are properly regulated to identify the extracted structures in Cloudcompare. To make it convenient to see the LiDAR points cloud to a large extent colourization was obtained. The LiDAR data that was imported into Cloudcompare was organized to show the top view to obtaining the segment in a rectangular form. The below figures show detailed explanations and analyses of the primitive structures extracted from LiDAR points cloud data with their parameters in Cloudcompare software.

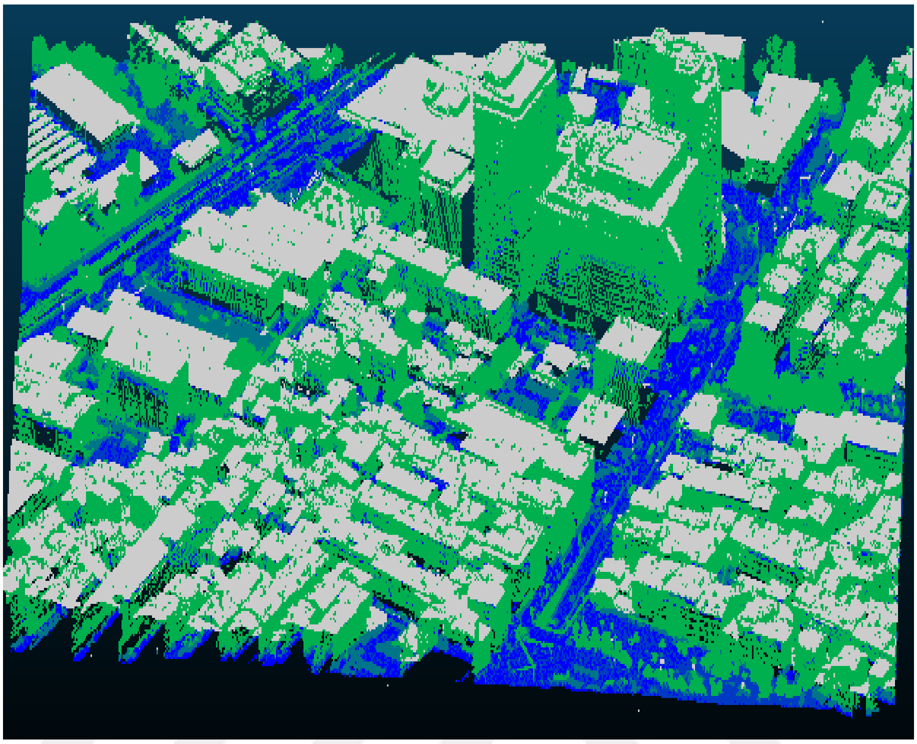

Figure 4.2. The segmented LiDAR points cloud of the test area in Cloudcompare software

Classes 🟩 Vegetations 🟦 Ground 🟩 Buildings

Others

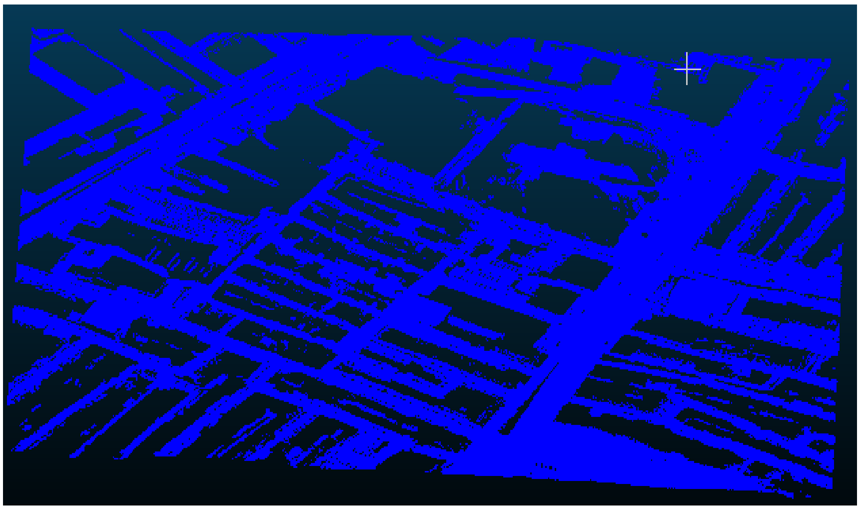

Figure 4.3.The Ground of test area in Cloudcompare software

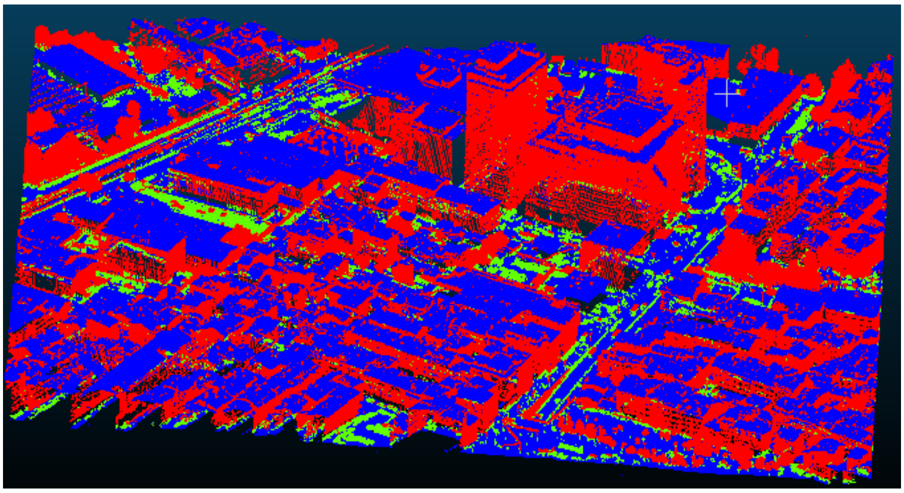

Figure 4.4. The segmented LiDAR points cloud of test area showing vegetations, ground, buildings, and others in Cloudcompare software

Classes 🟩 Vegetations 🟦 Ground & Rooftop 🟥 Buildings

Others

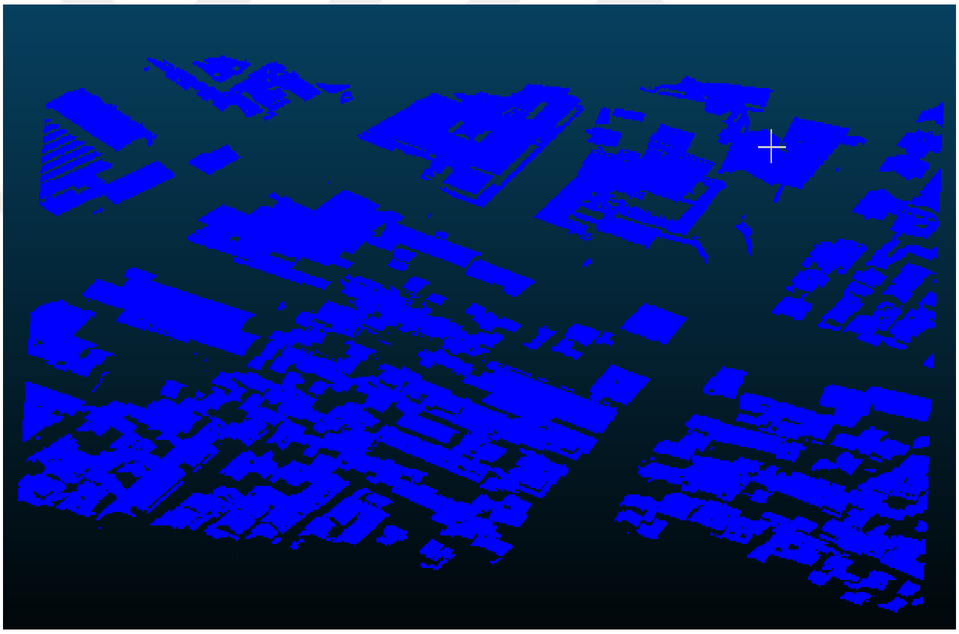

Figure 4.5. Rooftops of classified buildings in the test area from Cloudcompare software

Table 4.1. Parameters of display area with minimum and maximum filter points by values in Cloudcompare

Ground display range	2.00000000	5.01935484
Min / max values	1.00000000	2.50000000
Vegetation	2.54516129	5.56451613
Min / max values	2.50000000	5.50000000
Buildings	5.52258065	6.61290323
Min / max values	5.52258062	6.61290312

We remark that Cloudcompare allows the optimization of Segmentation and Classification of various types of buildings, roads, the ground, and many more. In this thesis, CloudCompare gave us an option to globally shift all LiDAR point clouds so that no numerical precision is lost when displaying the point cloud within the viewer.

Mathematically, the global shift and global scale encode the transformation between the original (global) coordinate system of the entity and the working local) coordinate-system (Girardeau-Montaut, 2015). Assuming that $\boldsymbol{T}(x, y, z)$ be the global shift (translation), S be the global scale, and P a 3D point, shows that the coordinate of the local 3D point is equal to the total sum of the global coordinate of the 3D point plus the global shift (T) multiply by the global scale (S) or equivalently, the global coordinate of the 3D point is equal to the sum of the coordinate of the local 3D point divided by the global scale (S) and in the end subtract the global shift (T) from the sum of the coordinate of the local 3D point divided by the global scale (S).

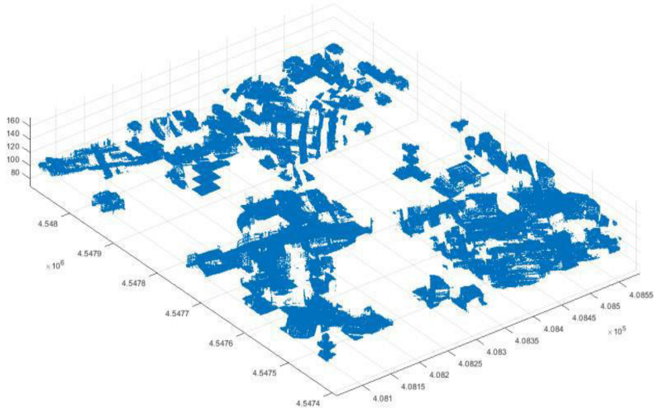

Figure 4.6.Rooftops of classified buildings in the test area from Matlab software

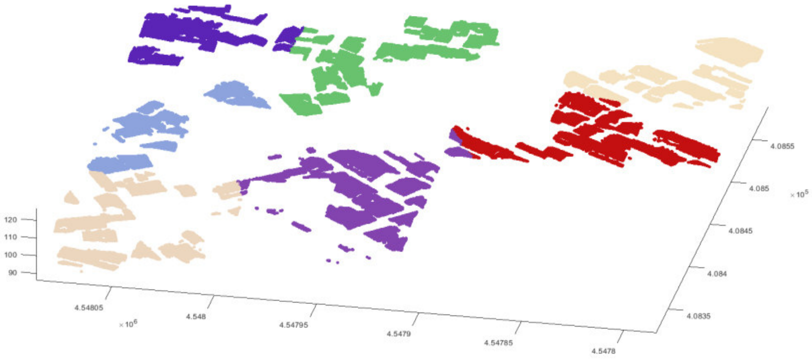

Figure 4.7.Rooftops of filtered buildings only in the test area from Matlab with the proposed method

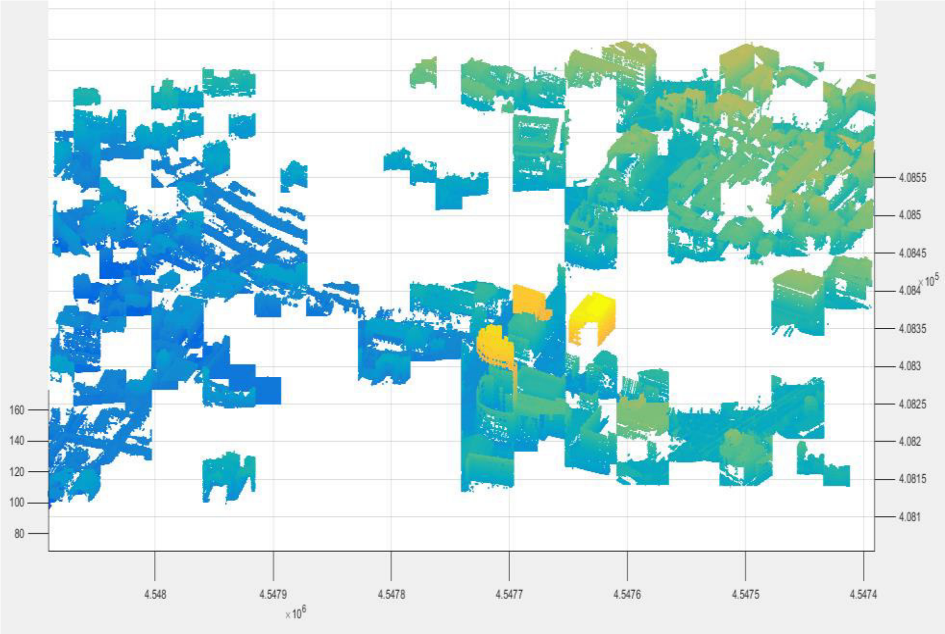

Figure 4.8.The random segmented LiDAR points cloud of test area showing height, the rooftop of buildings, and others in Matlab software

Figure 4.8 above shows an automatic extraction of buildings that were obtained in Matlab software. The RANSAC algorithm is robust since the data is huge it iterated the LiDAR point cloud to extract objects that are reasonable enough. From the figure, the height and rooftop of the buildings are viewable.

Table 4.2. Examples of rooftop parameters in Matlab

a	b	c	d
-0.0293	0.0396	0.9987	-168613.22
0.0269	-0.0408	-0.9988	175049.69
-0.0314	0.0360	0.9988	-151114.30
-0.0310	0.0376	0.9988	-158811.23
-0.0305	0.0402	0.9987	-170853.74
-0.0264	0.0403	0.9988	-172796.69
0.0280	-0.0436	-0.9986	187283.01

Table 4.3.Examples of Rooftop normal vectors in Matlab

a	b	c
-0.0293	0.0396	0.9987
0.0269	-0.0408	-0.9988
-0.0314	0.0360	0.9988
-0.0310	0.0376	0.9988
-0.0305	0.0402	0.9987
-0.0264	0.0403	0.9988
0.0280	-0.0436	-0.9986

Table 4.2 and Table 4.3 above represents an example of rooftop parameters and an example of rooftop normal vectors in Matlab with the proposed method. In this thesis, the two results in Table 4.2 and Table 4.3 were obtained in our code from a model that returns the point cloud fit plane (model = pcfitplane). In Matlab, finding the plane the m-estimator Sample Consensus (MSAC) algorithm is used. RANSAC is a variant of the MSAC algorithm. Plane parameters, specified as a 1-by-4 vector. This input specifies the Parameters property. The four parameters $[a, b, c, d]$ Table 4.2 describe the equation for a plane, equation (1.1) in the plane extraction section of this thesis. The rooftop normal vector of the plane in this thesis, stored as a 1-by-3 vector. The $[a, b, c]$ Table 4.3 describes a vector that specifies the unnormalized normal vector of the plane, equation (3.2) in the mathematics of the proposed method of this thesis. An intermediate plane is always a horizontal plane parallel to the top/bottom reference level of a story and is defined for a selected (active) story (building). Because it allows defining structure elements positioned between the bottom and top levels of a story, the intermediate plane is an alternative to defining offsets while creating structure elements (walls, columns, beams) and many more.

In mathematics, a plane is a flat, two-dimensional surface that extends infinitely far. A plane is the two-dimensional analogue of a point (zero dimensions), a line (one dimension), and three-dimensional space. Planes can arise as subspaces of some higher-dimensional space, as with a room's walls extended infinitely far, or they may enjoy an independent existence in their own right, as in the setting of Euclidean geometry (Weisstein, 2002).

4.1. Comparison and Verification of Experimental Data

Accuracy is our main priority at this stage. To confidant of our approach to LiDAR data, Terrestrial Laser Scanner (TLS) data were obtained in Cloudcompare software and Matlab to determining that a model implementation accurately represents the later conceptual description of the model and the solution to the model. The test result shows reasonable to validate the efficiency of our approach.

Figure 4.9.TLS Original view of a building front face

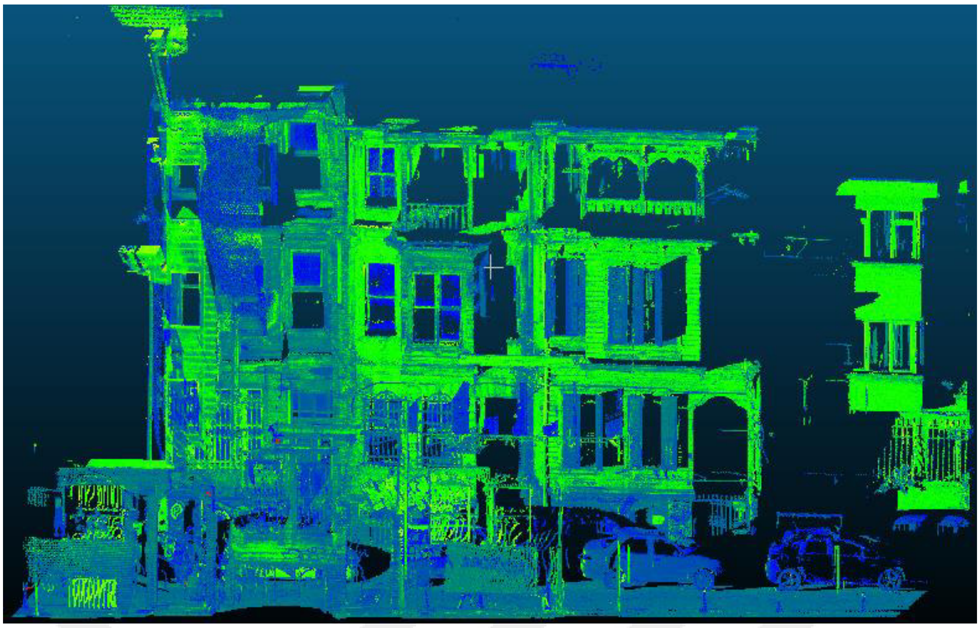

Figure 4.10.TLS Cloudcompare view of a building front face

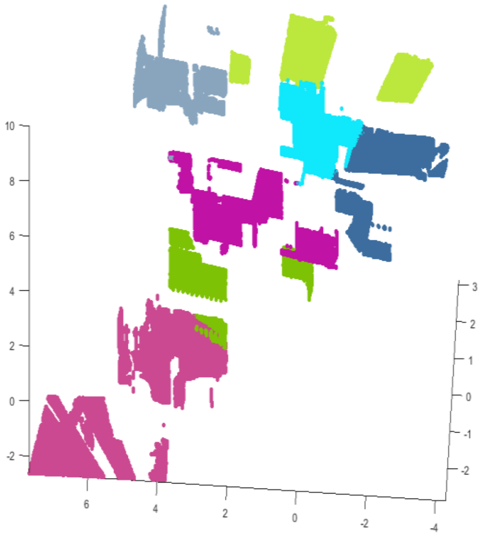

Figure 4.11.TLS Matlab view of the building

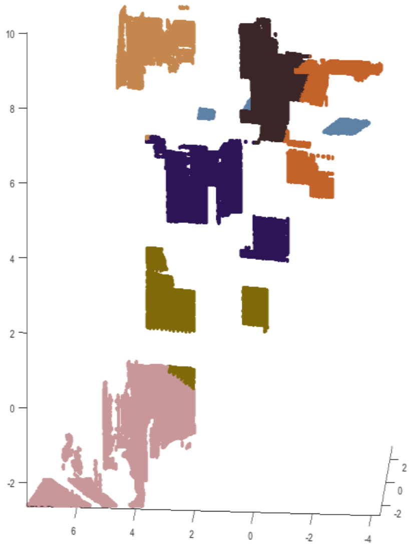

Figure 4.12.TLS Matlab view of the building after the first iteration

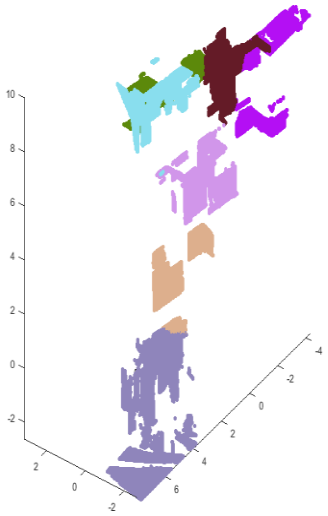

Figure 4.13.TLS Matlab view of the building after the second iteration

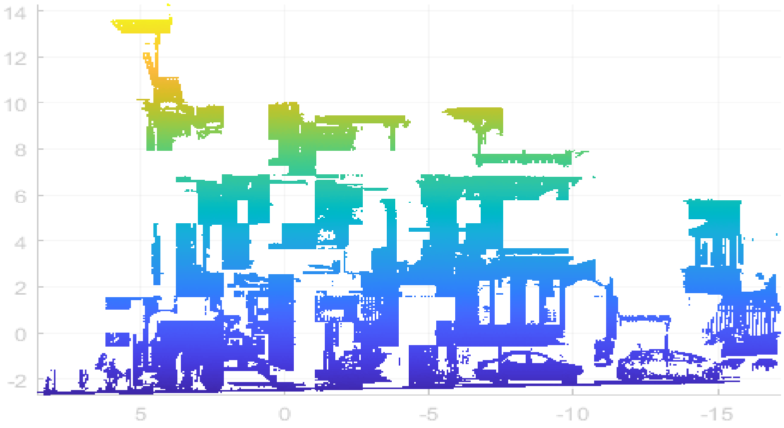

Figure 4.14.TLS Matlab view of the building after the third and final iteration

Figure 4.13 is the final iteration of TLS that shows the planar feature of the test building. As said earlier, the result obtained is reasonable enough which is the main focus of iteration. We remarked that our method is proactive in the extraction of a plane from LiDAR point clouds. It is summarized that our method is better to compare to the state-of-the-art.

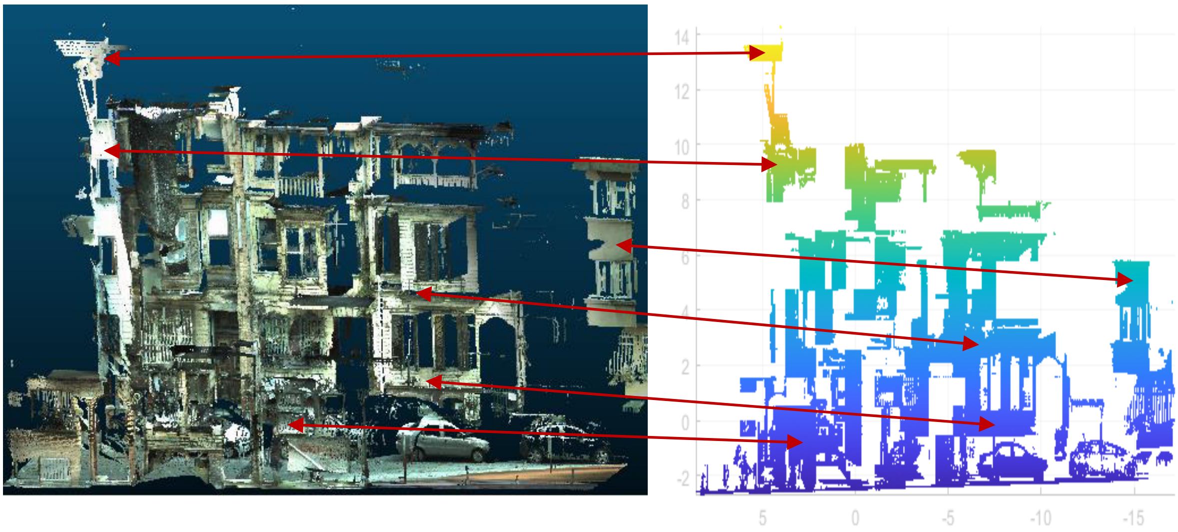

Figure 4.15.Matching the test building of TLS in Cloudcompare view to Matlab view after the third and final iteration

To be more confident we matched the Cloudcompare view of the TLS to that of the Matlab view. Because the data is huge RANSAC algorithm may extract the wrong plane due to complex geometry, but in this thesis work, the result obtained is reasonable.

Table 4.4.Examples of a building front face parameters in Matlab

a	b	c	d
-0.9849	0.1661	0.0480	-8.7034
-0.9620	0.2151	0.1676	-8.5395
-0.9559	0.1958	0.2185	-8.4268
-0.9683	0.1971	0.1533	-8.5214
0.9800	-0.1708	-0.1016	8.6432
-0.9919	0.1053	0.0708	-8.6674
0.9788	-0.1907	-0.0739	8.7050

Table 4.5. Examples of a building front face normal vectors in Matlab

a	b	c
-0.9849	0.1661	0.0480
-0.9620	0.2151	0.1676
-0.9559	0.1958	0.2185
-0.9683	0.1971	0.1533
0.9800	-0.1708	-0.1016
-0.9919	0.1053	0.0708
0.9788	-0.1907	-0.0739

Table 4.4 and Table 4.5 above represent examples of the experimental TLS building front face parameters and examples of its front face normal vectors in Matlab with the proposed method. In this thesis, the two results in Table 4.4 and Table 4.5 were obtained in our code from a model that returns the point cloud fit plane (model = pcfitplane). In general, finding the plane the m-estimator Sample Consensus (MSAC) algorithm is used. Plane parameters, specified as a 1-by-4 vector. This input specifies the Parameters property. The four parameters $[a, b, c, d]$ Table 4.4 describe the equation for a plane, equation (1.1) in the plane extraction section of this thesis. The building faces the normal vector of the plane in this thesis, stored as a 1-by-3 vector. The $[a, b, c]$ Table 4.5 describes a vector that specifies the unnormalized normal vector of the plane, equation (3.2) in the mathematics of the proposed method of this thesis.

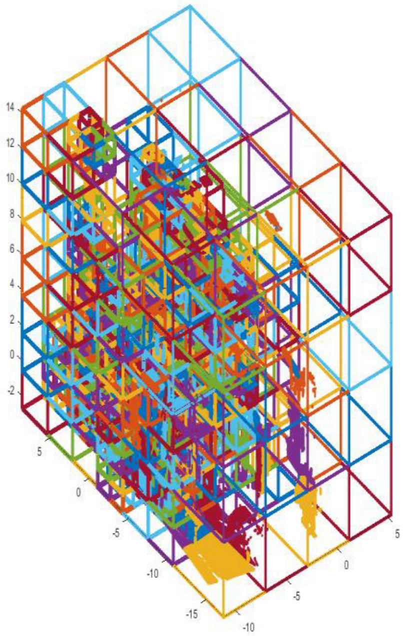

Figure 4.16.LiDAR point cloud OcTree segmentation of a building front face

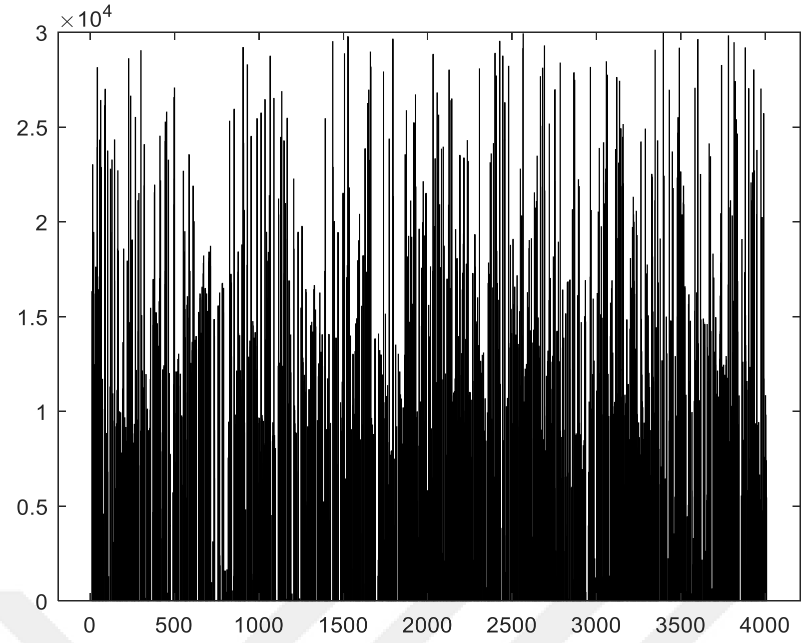

Figure 4.17.TLS Matlab LiDAR point cloud data histogram of a building front face

The test site in TLS contained a single building with parking cars, shops, and bare ground in front. The primary objective of obtaining the TLS data is to investigate how the extracted image from the LiDAR point clouds appear using the Segmentation and Classification approach of images in both Matlab and cloudcompare software. Easily identifiable structures figure 4.15, figure 4.16 and figure 4.17, their intended functionality or as a direct result of their design often exhibit strong and real-life man-made objects. The arrangement of figures typically appears in the form of individual parts. Understanding the scene and be knowledgeable about the object structure is an important cue for object recognition. At an angle of 360^0 TLS capture prominent ground details whereas the LiDAR survey gathers a huge amount of details data including building rooftop and trees top that TLS can not collect. This recent technique in technology plays an important role in the diverse field of the present world. To be more confident in our approach we obtained the TLS for proper analysis. Both the TLS and the LiDAR point cloud have different point densities.

5. FUTURE WORK

Random Sampling Consensus (RANSAC) algorithm is the approach in the extraction of Planar Objects from LiDAR Point Cloud Data. Due to the challenge in figuring the RANSAC algorithm in Matlab, we decided to continue with this research using the RANSAC algorithm in our spare time that we would reorganize and expand the idea after the PhD. RANSAC is one of the most attractive techniques in fitting and extracting a plane. A minimal sample set (MS) is obtained at random and iterated until a reasonable result is reached. To extract a large percentage of an outlier and small parameter estimation RANSAC is the most suitable technique. The RANSAC technique is regularly applied to registration, detection, feature matching and many more for parameter model estimation.

Chapter 3 of this thesis that RANSAC is part of the state-of-the-earth-methods, however, the RANSAC algorithm is still robust than ever. RANSAC was introduced by Fischer and Bolles (Bolles & Fischler, 1981) and is widely used for shape detection (Li et al., 2017; Schnabel et al., 2007; Xu, Jiang, Shan, Zhang, & Li, 2016). The RANSAC algorithm mainly involves performing two iteratively repeated approaches on a given LiDAR point cloud: generating a hypothesis and verification. Step I, obtaining a Minimal Sample Set (MSS) of ‘A’ that we referred to as hypothesis; for example, obtain RANSAC operation that it is an iterative approach select 3 points or more from "A", calculate the distance inliers taking into consideration cosine of their angles, delete outliers from the region of interest, export activated points to file, pcfitplane: fits a plane to a point cloud that has a specified maximum angular distance, show figure. To show an extracted plane from this approach would be the actual target in our future research (Model-Based Methods). Step II, the entire points in the LiDAR point clouds would be tested obtaining an approach referred to as Consensus Sampling (CS) with the resulting candidate shapes to determine how many of the points are well approximated by the model. After a certain number of iterations, the shape that possesses the largest percentage of inliers is extracted and the algorithm continues to process the remaining data. The plane is often fitted by the least-squares (LS) method, but this approach is often not robust to outliers when detecting planes repeatedly (Li et al., 2017).

5.1. Inlier and Outlier

The mean closer to reality is referred to as inliers. The inlier is a value that raises no eyebrow. However, (Evans, Feng, & Peterson, 2001) point out that a large number of a variable are unlikely to lie closer to the mean. Outliers are a huge challenge compared to inliers. The outlier detection in our proposed research obtains the LiDAR point clouds data that do not go in line with the behaviour of the whole LiDAR data. The whole scenario of outliers depends on the targeted model to be extracted, they can be very different. Our goal will be to remove 50 per cent or more outliers while retaining the large majority of inliers (reasonable enough). Reconstruction only occurs to the part that contains scientific data and outliers that are closer to the true value are easily handle before the 3D reconstruction approach (Blaha et al., 2016; Hane, Zach, Cohen, Angst, & Pollefeys, 2013).

The Outliers in LiDAR point clouds and noise elimination in automatic detection approach is long-standing and still an active research area (Yu, Lau, Cheng, & Cui, 2017). Our target application in future research is plane extraction from the LiDAR point cloud data was obtained from İstanbul Turkey and the data belongs to "İstanbul city council municipality Test Project on Urban Classification" and any other data that might be of interest.

5.1.1. Iteration

The process of obtaining a reasonable result is referred to as iteration. The algorithm is repeated many times till a condition is met reasonable enough. In this thesis, the iteration value for the plane segmentation filter of the LiDAR point clouds in our future research will have a large impact on the processing time to comply with the modern days' advancement in obtaining planes. Iterations change the number of internal iterations to attempt to find a match, increasing the number only serves to increase the chances of finding a better match. So long as the number will be above a minimum value, the results should be more or less the same. Due to the number of iterations, we will consider the plane that has the best inliers. Points that form a plane will discover that should be RANDOM because if they are parallel there will be no result for plane formation. We will do a point selection of three points or more from the LiDAR point clouds to know whether they are parallel using two vectors. If the two vectors prove to be parallel, it means that plane can not be formed. The target is to obtain a reasonable result, we will continue with the iteration process till arriving at a point wherein majorities of the inliers will be at high precision.

5.1.2. Extraction of Other Primitive Shapes

In our research, we will present the automatic, semi-automatic algorithm in obtaining basic shape structure in unorganized LiDAR data. We used the algorithm to break down the LiDAR data that the inliers remaining is evident to reality. Obtained points easily find their matches. Our proposed approach would rely mainly on RANSAC plane extraction like spheres, cylinders, cones, tori, and many more. The target will include a simple shape structure model that represents the whole structure at random. The research will be sensitive to outliers and a high degree of noise. Our algorithm will be iterated till a point is met that is closer to reality. Implemented fields will include LiDAR point clouds survey and extraction of artificial primitive structures. Our research will focus especially on finding an efficient algorithm for LiDAR point clouds extraction of artificial structures.

5.1.3. 3D Cylindrical Surface Model

In our future research, we will obtain a cylindrical fitting approach to estimate the initial values of cylindrical parameters using the LiDAR point clouds to estimate the normals of the cylinder. For all data points in the cylindrical LiDAR point clouds, a certain number of neighbourhood points will be selected to estimate the normal direction of the point, for example, Figure 5.1

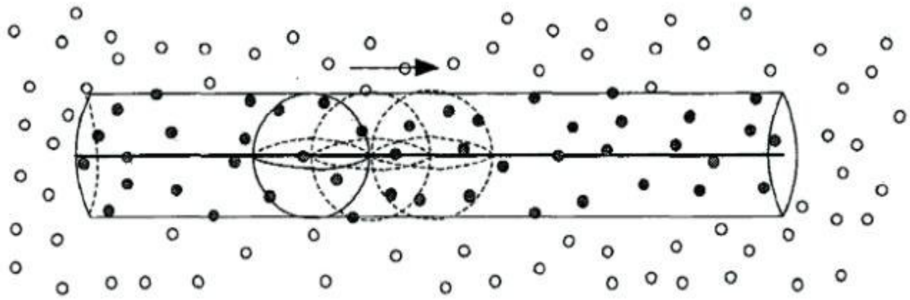

Figure 5.1. Neighbourhood point cloud search schematic. For any data point in a cylinder, a certain number of neighbourhood points are selected for normals estimation (Stoel & Geary,2018)

The next step will be estimating the normal line of the scanned point, the initial values of the axis direction vector will be calculated by obtaining the least square approach according to the vertical relation between the normal direction of the point and the axis direction of the cylinder, and then the initial values of a point and the cylindrical radius on the axis of the cylinder will be calculated by coordinate transformation and the round least square fitting. Next, obtaining the initial values of all cylindrical parameters, the number of parameters, we will obtain the RANSAC algorithm for the iterative approach to reduce any constraints that might occur in the extraction of the cylinder.

The normals estimation approach in our future research will be based on the nearest neighbour point directly infers the surface normals according to the coordinates of data points in the point cloud. That is, the covariance matrix of the point will be established in the three-dimensional LiDAR point clouds, and the normal direction (Calderon & Boubekeur, 2014) of the point will be estimated approximately by covariance analysis. Mathematically, any point P in the LiDAR point clouds the corresponding covariance matrix C will be equation (5.1) and (5.2) below;

$$C = \frac{1}{k}\sum_{i=1}^{k}(p_i - \vec{p}) \,.\, (p_i - \overline{p})^T \tag{5.1}$$

$$C * \vec{v}_t = \Lambda_t * \vec{v}_t, t \in \{0,1,2\} \tag{5.2}$$

Where k in equation (5.1) referred to the number of nearest neighbour points of the selected point $P * \overline{p}$ is the three-dimensional centroid of the nearest neighbour point of point P , Λ_t is the t eigenvector corresponding to the values of the first eigenvalue Since the LiDAR point clouds will be huge we will be obtaining an octree approach to divide the LiDAR point clouds into the smaller segment.

The eigenvectors and eigenvalues of the covariance matrix are analyzed, and the eigenvector $\vec{v}_0$ which corresponded to the minimum eigenvalue Λ_0 of the covariance matrix C is solved, that is, the normal vector direction of the point P. The obtained normal vector has two meanings; that is, it cannot determine whether it is positive or negative of the point cloud estimation method vector, but because the vector initial values of the axis direction are solved by the vertical relationship with the surface normal vector of the point cloud, it is estimated that the two senses of the point cloud normals vector do not affect the estimation of the initial values of the cylindrical axis.

5.1.4. 3D Spherical Model

In our future research of 3D spherical model extraction from LiDAR point clouds, all points on the spherical surface will have the same distance from the centre of the sphere, and the normal vector of those points will be towards the centre of the sphere. $S_c(X_c, Y_c, Z_c)$ would be obtained to be the sphere's centre coordinates and the radius S_R of the sphere that will determine the position of the sphere. Based on the geometry of the sphere, the spherical model would be represented by equation (5.3) (Wong, Schnieders, & Li, 2008) below;

$$\begin{cases} P_1 - S_c = S_R\, n_1 \\ P_2 - S_c = S_R n_2 \end{cases} \tag{5.3}$$

Where centre coordinates S_c and radius S_R of the sphere would be obtained by substituting points $p_1\,(x_1, y_1, z_1)$, $p_2\,(x_2, y_2, z_2)$, and their normal vectors $n_1\,(x_{n1}, y_{n1}, z_{n1})$, $n_2\,(x_{n2}, y_{n2}, z_{n2})$ into equation (5.3).

Our future obtains sphere will present the points that estimate the centre axis and radius of the cylinder. Example Figure 5.1 shows a sphere with the same diameter as the cylinder moving along the inside of the cylinder, leaving a trace of the centre point. In the LiDAR point clouds, a centre point and a radius would be calculated, as shown in Figure 5.1, if it performs spherical fitting through neighbouring points around a point.

The mathematical model of the sphere (Calloway, 1965) is shown in equation (5.4), and the parameters a, b, c, and r would be determined through RANSAC to calculate the radius and centre of the sphere.

$$x^2 + y^2 + z^2 - 2ax - 2by - 2cz + a^2 + b^2 + c^2 - r^2 = 0 \tag{5.4}$$

Equation (5.4) will become the determinant equation (5.5) and parameters could be determined through the pseudo-inverse of equation (5.6).

$$\begin{bmatrix} x_1 & \cdots & y_1 & z_1 & 1 \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ x_n & \cdots & y_n & z_n & 1 \end{bmatrix} \begin{bmatrix} -2a \\ -2b \\ -2c \\ a^2 + \quad b^2 + \quad c^2 - \quad r^2 \end{bmatrix} = \begin{vmatrix} -x_1^2 & -y_1^2 & -z_1^2 \\ \vdots & \vdots & \vdots \\ -x_n^2 & -y_n^2 & -z_n^2 \end{vmatrix} \quad \textbf{(5.5)}$$

$$A^{+} \, (A^{T} \;\, A)^{-1} \, A^{T} \quad \textbf{(5.6)}$$

6. CONCLUSION

In this thesis, we have presented the Model-based methods in the extraction of Planar Objects from LiDAR Point Cloud Data. The Model-based method is a mathematical model that uses the RANSAC algorithm in the fast acquisition of a plane. The LiDAR point cloud is so huge that the RANSAC algorithm uses an iterative means to obtain a plane. RANSAC algorithm extracts only a single plane at a time. With the RANSAC algorithm, the plane obtained is similar to reality. Although our algorithm, in contrast to other previous methods in photogrammetry and computer graphics since we had some challenges in obtaining planes because of the complex geometry of the huge LiDAR point cloud, we stress that this is not a requirement in many applications. The speed of the method, the quality of the results, partitioning of the data, and other requirements on the LiDAR point cloud present our algorithm as a practical choice in obtaining the artificial structure of the LiDAR point cloud in many areas.

We obtained an Octree approach for fast and accurate segmentation of the LiDAR point cloud. The octree approach is a simple means of partitioning multiple homogeneous LiDAR point clouds into a suitable segment. To partition the points into segments, we considered their nearest neighbours.

In recent years, the idea of numbers of mega-cities transforming into 3D photorealistic virtual models to support the decision making process for maintaining the cities' infrastructure and the environment more effectively. 3D virtual city models are static snap-shots (scan) of the environment and represent the status quo at the time of their data acquisition. However, cities are dynamic systems that continuously change over time. Accordingly, their virtual representations need to be regularly updated promptly to allow for accurate analysis and simulation results that decisions are based upon.

The concept of "continuous city modelling" is to progressively reconstruct city models by accommodating their changes recognized after the automatic extraction processes, while preserving unchanged structures. RANSAC algorithm is also used in obtaining this goal.

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