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# LiDAR Systems and Its Applications for 3D City Modeling: A Review

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**Abstract**

*LiDAR (Light Detection and Ranging) is an advanced remote sensing technique that employs laser technology. It has diverse applications across various fields, including 3D city modeling, environmental and urban planning, and decision-making processes. 3D city modeling applications of LiDAR include 3D city information such as building reconstruction, solar power potential assessment, change detection, urban transport system, flood inundation modeling, urban vegetation and urban and peri-urban forest, urban land cover classification and extraction of power lines. Access to x y z of 3D city offers opportunities to derive a wealth of information about building, solar power potential of roof planes, changes in buildings and other structures, urban transport systems, urban flooding, urban vegetation and urban and peri-urban forest, urban land cover and urban power lines. The review paper focuses on critical aspects such as feature extraction, segmentation, object recognition, classification algorithms, and deep learning methods related to LiDAR. Additionally, it explores how LiDAR data can be applied effectively in creating detailed 3D models of cities.*

Keywords: *3D city modeling, laser scanning, LiDAR.*

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## Introduction

A 3D city model is a representation of an urban environment with a three-dimensional geometry of common urban objects and structures, with buildings as the most prominent feature (Biljecki et al, 2015). They are either based on photogrammetry or on LiDAR (Light Detection and Ranging) or on a combination of both data acquisition techniques (Dorninger and Pfeifer, 2008). Gupta (2015) also stated that 3D city models are the digital representation of the earth's surface and related natural, cultural and manmade objects of the urban areas like buildings, trees, vegetation, podiums, etc. 3D city models could also be applied for climatic modeling, disaster management and mapping of buildings as well as study of urban built environment. 3D city modeling is important in many operational applications, such as urban planning and management, vehicle navigation and radio frequency signal propagation which are of increasing importance in modern society urban environments. 3D city models are also essential for supporting numerous management applications

(Dorninger and Pfeifer, 2008). In this regard, information for a 3D city model may be acquired from aerial photographs or satellite imageries using photogrammetric techniques. In recent times, LIDAR systems have seen growing use in complex modelling requirements (Pal Singh et al., 2013). LIDAR, an active remote sensing technology, calculates distances by multiplying the speed of light with the time taken for a laser pulse to travel to a target object (Lim et al., 2003)

LiDAR techniques have been researched and utilized since the early 1960s but seem to have become more prominent in the past few years. One of the earliest LiDAR applications was to study the atmosphere in 1963 by Fiocco and Smullin (Measures, 1984). However, the use of LiDAR data for 3D modeling of urban areas has gained more attention in recent years. One important reason that the applications of LiDAR technology to terrain models and topographic mapping are increasing is its integration with Global Positioning System (GPS). Consequently, applications of the LIDAR systems have developed recently through parallel advances in GPS and inertial navigation systems (INS) (Lim et al, 2003).

The collection of 3D data using LiDAR has several advantages over most other techniques. Chief among them are higher resolutions, high vertical accuracy (centimeter accuracies), fast data collection and processing of robust data sets with many possible products and the ability to collect data in a wide range of conditions and ground detection in forested terrain (NOAA, Coastal Services Center, 2012). Rönnholm et al. (2009) also noted that LIDAR has become popular due to its fast 3D point cloud acquisition, improvements in post-processing software and high usability of the data generated. LiDAR technology serves as an accurate survey tool for obtaining highly accurate datasets. Airborne laser scanning is a rapid, highly accurate and efficient method for capturing 3D data of large areas. However, the quality of LiDAR data depends upon the sampling and filtering methods (Charlton et al., 2003).

LiDAR’s versatility and high resolution make it valuable for various purposes, including atmospheric science (Devara and Rai, 1993; Wang & Menenti, 2021), bathymetric data collection (Mandlburger et al., 2015; Pan et al., 2015), law enforcement and telecommunication (Cerreta et al., 2020; Carreon-Limones et al., 2017). Currently, LiDAR data are playing a key role in, urban and environmental planning and decision-making, modern navigation systems and some engineering projects as well as other disciplines and applications require 3D data (Rönnholm et al, 2009). 3D city modeling applications of LiDAR include modeling rail way environments (Zhu and Hyyppa, 2014; Gézero, & Antunes, 2019 ), modeling urban park and trees(Omasa et al., 2007; Heo et al., 2019 ); extracting urban features from LiDAR DSM (Wang & Li, 2020); building reconstruction (Pu and Vosselman, 2009; Elberink and Vosselman, 2009; Yan et al., 2016; Jung et al., 2017); integration of aerial thermal imagery, LiDAR data and ground surveys for surface temperature mapping (Mandanici et al, 2016); solar potential assessment ((Jochem, et al., 2009; Mansouri et al., 2019); Jochem et al.,2011 and schuffert et al., 2015); and rooftop surface temperature analysis (Zhao et al., 2015), as well as road surface modeling (Jaakkola et al., 2008; Wu et al., 2019) and extraction of urban power lines from vehicle-borne LiDAR data (Cheng et al., 2014).

The point cloud data produced from various LiDAR systems is the key data source of the application of LiDAR system in 3D city modeling. However, there are very few discussions of the feature extraction and segmentation algorithms, object detection and classification methods. Hence, in this review we attempted to incorporate the recent developments for processing and feature extraction of point cloud data such as features extraction and segmentation, object recognition and classification algorithms, and deep learning methods. Thus, the objective of this paper was to provide a review of the data processing and feature extraction algorithms and applications of LiDAR systems for 3D urban modeling. Specifically, it is a short description of LiDAR systems and its applications in 3D modeling of urban areas. The remainder of this paper is organized as follows. Section two presents and reviews feature extraction and segmentation algorithms. The third and fourth sections presents object recognition and classification algorithms and deep learning methods respectively. The fifth section presents selected applications of LiDAR systems in 3D city modeling. Finally, conclusions and future outlook are presented in section six.

**Feature Extraction and Segmentation**

Feature extraction involves identifying relevant attributes or characteristics from data. In the context of LiDAR point clouds (or any other data), it aims to extract specific information that helps differentiate between different points or objects. Low-level attributes, such as location, elevation, geometry, color, intensity, and point density, are considered during feature extraction. These attributes lack semantic meaning on their own but provide essential information about the data. By extracting features, we create a set of measurements that can be used for pattern recognition, classification, or further analysis. For example, we might extract features related to edge smoothness or other geometric properties. On the other hand, segmentation involves grouping data points based on their low-level attributes. It partitions the data into segments or objects. In the case of LiDAR point clouds, segmentation identifies regions with similar characteristics. These regions could correspond to individual objects (such as trees, buildings, or cars) or parts of larger objects. Once we have segments, we can perform more detailed analysis on each one (Chen et al., 2019). Segmentation provides richer information about the objects or segments compared to analyzing each point individually. Che et al. (2019) discusses various methods for feature extraction and segmentation in LiDAR point clouds. Some of these methods include: Hough Transform, Random Sample Consensus (RANSAC), Principal Component Analysis (PCA), Fast Point Feature Histograms (FPFH), Region Growing and Connected Components, Graph-Cut, super voxelization.

In their research, Li et al. (2012) introduced a novel algorithm that employs a top-to-bottom region growing approach to segment individual trees sequentially, starting from the tallest to the shortest. The study focused on mixed conifer stands with similar structural characteristics, utilizing small footprint, discrete return LiDAR data. The results indicated that the proposed algorithm has significant potential for accurately segmenting individual trees. Additionally, Vo et al. (2015) explored the feasibility of an octree-based region growing algorithm for precise and rapid segmentation of terrestrial and aerial LiDAR point clouds. Meanwhile, Zhao et al. (2016) proposed a point cloud segmentation method based on Fast Point Feature Histograms (FPFH). Their results demonstrated the effectiveness of this approach, which avoids both under-segmentation and over-segmentation issues.

Similarly, Gilani et al. (2016) in their study proposed a PCA point cloud segmentation technique for building detection and roof plane extraction and the results showed the robustness of the approach and the quality of the reconstructed surfaces and extracted buildings.

In another study, Xu et al. (2018) proposed a voxel - and probabilistic model-based method (VPM) to down sample large original point clouds to reduce the time costs of sequence processing and results showed that the proposed method outperformed representative segmentation algorithms, such as point- and voxel-based region growing, difference of normal based clustering, and LCCP. Li (2018) examined the feasibility of using embed super voxel-based nodes on a Riemannian graph and the experimental results showed that the technique can be effectively applied to the artificial point cloud in challenging circumstances. Jin & Lee (2019) in their study, proposed a fast Cylinder Shape Matching Using Random Sample Consensus (RANSAC) in Large Scale Point Cloud. The results demonstrated that the proposed method has enhanced the efficiency of the reverse design by matching linear and curved cylinder estimation without vertical/horizontal constraint and segmentation. Recently, Cheng et al. (2021) proposed an elaborate K nearest neighbor (KNN)-based segmentation method via an optimization strategy. The experimental findings indicate that the proposed technique effectively removes noise and outperforms several traditional methods in terms of denoising performance and processing speed.

## Object Recognition and Classification Algorithms

Urban environments contain a variety of objects including different types of buildings, transport, and other infrastructures such as roads, rail ways, electric poles, sewerage systems and manholes, green vegetation. However, its monitoring is traditionally conducted by visual inspection, which is time consuming and expensive. LiDAR systems such as terrestrial and aerial Mobile laser scanning (MLS) sample the urban environment efficiently by acquiring large and accurate point clouds. The developments of both terrestrial and aerial MLS systems, which provide LiDAR point clouds data, open a new opportunity for monitoring of urban environments. In this regard, several methods have been applied and developed for urban object recognition and classification (Huang & You; Wang et al., 2017; Huang et al., 2020; Zhu et al., 2017). For instance, Wang et al. (2017) proposed a 3D eigenvector-based shape descriptor using voxels (SigVox) - A 3D feature matching algorithm for urban road object recognition from mobile laser scanning point clouds. The results showed that the proposed approach was able to recognize street signs and lamp poles.

In their research, Huang and You (2015) introduced a system with three key stages: localization, segmentation, and classification to identify and categorize pole-like objects from point clouds captured in urban environments. The method's effectiveness was illustrated by comparing it to previous approaches using a comprehensive large-scale urban dataset. In another study, Huang et al. (2020) evaluated the performance of a sparse LSTM-based multi-frame 3D object detection algorithm. In this study the authors applied the U-Net style 3D sparse convolution network (CNN) to extract features for each frame's LiDAR point-cloud. The Experimental findings showed that the proposed algorithm outperforms the traditional frame by frame approach.

Rodríguez-Cuenca et al. (2015) investigated the potential application of an anomaly detection algorithm to identify and categorize vertical urban objects and trees using unstructured three-dimensional point cloud data from mobile laser scanners (MLS) or terrestrial laser scanners (TLS). Their results indicated detection rates exceeding 96% at the two test sites, with a classification accuracy of approximately 95% and a completion quality of 90% for both procedures. In another study, Zhu et al. (2017) explored the feasibility of employing a semantic classification technique by dividing spatial space into fixed-size voxels. This approach addressed the challenges associated with non-homogeneous density distributions in point clouds. The proposed technique achieved an average per-area completeness of 93.88% and correctness of 95.78%.

Kuang et al. (2020) developed a deep architecture using the Voxel-Feature Pyramid Network (FPN) for multi-scale voxel partitions. Their experimental results demonstrated competitive 3D detection outputs while significantly reducing time complexity, making it suitable for real-world inference tasks. In their study, Tian et al. (2019) designed a multilayer neural network-based 3D object recognition system that extracted multiple features from LiDAR point clouds. They pre-processed the data by extracting non-ground points and initializing a voxel model based on the valid range of the remaining point clouds. Aijazi et al (2013) proposed a super-voxel-based segmentation and classification method for 3D urban scenes. Their study yielded an overall segmentation accuracy (OSACC) of 87% and an overall classification accuracy (OCACC) of approximately 90%.

**Deep Learning for LiDAR Point Cloud Classification**

In recent year, deep learning (DL) has become one of the emerging topics in computer vision due to its effectiveness image segmentation. In this respect, Convolutional Neural Networks (CNNs) are the key architecture that has been used in DL methods for classifying an entire image dataset (Krizhevsky, et al., 2017). Due to the requirement of regular and structured data as input for most deep learning architectures (such as 2D images), point cloud data often needs to be transformed. This transformation can involve projecting/rasterizing the point cloud into images or voxelizing it into 3D grids (Che et al., 2019). In another study, Melotti et al. (2020) proposed multisensor fusion strategies (combining camera and LIDAR data) for object recognition. They employed a CNN network (specifically, Inception V3) to classify RGB images and LIDAR data. Additionally, Widyaningrum et al. (2021) introduced the point-wise deep learning method called Dynamic Graph Convolutional Neural Network (DGCNN).

In another study, Stanislas et al. (2021) compared two deep learning algorithms, the first is based on voxel-wise classification, while the second is based on point-wise classification. They evaluated the performance of the proposed approaches on a realistic dataset with the presence of fog and dust particles in outdoor scenes and; results showed an F1 score of 94% for the classification of airborne particles in LiDAR point clouds. Diab et al. (2022) in their study evaluated the possible application of DL models, categorized by the structure of the data they consume. The authors conclude that convolutional neural networks (CNNs) achieve the best performance in various remote-sensing applications while being light-weighted models, namely Dynamic Graph CNN (DGCNN) and ConvPoint. Özdemir et al. (2019) evaluated the feasibility of various machine learning algorithms for aerial point cloud classification, including three deep learning algorithms and one machine learning algorithm. The results illustrated that deep learning algorithms can reach better accuracies; however, it takes relatively longer time to train and evaluate the employed networks. Recently, Wen et al. (2021) developed a global-local graph attention convolution neural network (GACNN) for classifying 3D point clouds from aerial LiDAR system. Experimental results showed that the proposed model achieves a satisfactory F1 score of 71.5% and overall accuracy of 83.2%.

## Applications of LiDAR Systems for 3D City Modeling

LiDAR systems have become a rapidly expanding field in recent years with particular significance in the treatment of 3D point cloud information for scientific, commercial and operational applications. In this regard, In the past years, there has been a considerable amount of research on 3D modeling of urban environments using LiDAR point cloud data (Sirmacek and Lindenbergh, 2015; Krizhevsky et al., 2017; Che et al., 2019). In several studies, it was demonstrated that LiDAR systems are useful to derive a wealth of information for 3D city modeling (pu and Vosselman, 2009; Elberink and Vosselman, 2009; Yan et al., 2016; Jung et al., 2017; Mandanici et al, 2016; Jochem et al., 2009; Jochem et al., 2011; schuffert et al., 2015; Zhao et al., 2015; Lafortezza and Giannico, 2019; Peng et al., 2017). In the following subsections applications of LiDAR systems in 3D city modeling is described in more detail.

### Building Reconstruction

One of the key components of any 3D City Model is a three-dimensional representation of the buildings present in the scene; the process of creating these 3D building models that include a geometric three-dimensional representation of roof and facades details is often referred to as building reconstruction. Building reconstruction is of primary importance in several applications, ranging from urban planning and telecommunication network propagation studies to applications for next generation vehicle navigation (Kokkas, 2009). In recent years building modeling and visualization have seen progress, where researchers, have used LiDAR data for the extraction of buildings and to obtain 3D reconstructions of buildings (Haala and Brenner, 1999; Zhu et al, 2011; Zhang et al., 2014; Elberink and Vosselman, 2009; Pu and Vosselman, 2009; Wu et al., 2017).

In their research, Rottensteiner et al. (2005) investigated building detection using LiDAR data and multispectral images based on Dempster-Shafer theory. Their findings were satisfactory: approximately 95% of buildings larger than 50 square meters could be detected, with about 89% of those detections being accurate. However, detection rates significantly decreased for smaller building structures (below 30 square meters). More recently, Wu et al. (2017) proposed a graph-based approach that utilized hierarchical structure analysis of building contours from LiDAR data to reconstruct urban building models. The results demonstrated successful reconstruction of complex buildings, with a mean modeling error of 0.32 meters.

Li et al. (2016) conducted a study on extracting and simplifying building facade pieces. They proposed a 3D LIDAR point cloud segmentation method combined with side-view projection based on highprecision POS data. By transforming the point cloud through projection, they effectively enhanced building facade features. Subsequently, they analyzed side-view projection image features and building facade traits. Their proposed method utilized morphological filtering for building facade extraction, ultimately achieving precise 3D building facade reconstruction. Notably, this approach is feasible for most city buildings, requires less computational workload than full point cloud processing, and relies solely on driving and recording data from roads.

Awrangjeb et al. (2010) also introduced an automatic building detection technique using LIDAR data and multispectral imagery. Their study demonstrated that the proposed technique successfully detects urban residential and industrial buildings of various shapes with a very high success rate. However, the method may exhibit limitations in areas with high-terrain slopes or dense high-rise buildings of rapidly varying height within a given tile size. In such cases, the average digital elevation model (DEM) height may not accurately correspond to the actual ground height. Similarly, Kabolizade et al. (2010) proposed an improved snake model for automatic building extraction from aerial images and LiDAR data. Their results indicated that this algorithm outperformed the traditional snake model by converging more quickly and stably to true building contours, especially in complex urban environments.

Alexander et al. (2009) also conducted research to visualize an urban area (Portbury near Bristol, England) by combining building footprints and LiDAR data. They found that high density LiDAR yielded the highest overall accuracy of building type detection, yet lower densities proved more useful for revealing overall roof morphology. Airborne Laser Scanning (ALS) data was used by Sirmacek and Lindenbergh (2015) to obtain 3D building models automatically. With the use of an active shape fitting-algorithm the authors proved the possibility of using the algorithm when simple and easy-to-render 3D models of large cities are needed. The method developed by Yan et al. (2017) used hierarchical segmentation, named LS-ORTSEG. The method was proposed to enhance the performance of a model-free framework for building 3D reconstructions.

Pu and Vosselman (2009) also studied the possibility of using terrestrial laser points for 3D feature extraction (building façade reconstruction) using semiautomatic building facade reconstruction approach. Another approach using target-based graph matching algorithm was applied by Elberink and Vosselman (2009) to automatic building reconstruction from laser data. The matching algorithm filters out segments and intersection lines did not match completely of a target. About 20% of the buildings were affected by segments that did not completely match the target graphs. In a few of these cases, this was correct because the segment was not representing a roof face. But, in about 40% of the cases, a neighboring segment that would complete a target match was missing. Dorninger and Pfeifer (2008) also proposed a comprehensive approach for the automated determination of 3D city models from airborne laser scanning point cloud data. In another study Song et al., (2020) proposed a framework for building reconstruction by using assembling and deforming geometric primitives, and the experimental results showed the effectiveness of the proposed method. More recently, Kulawiak, (2022) using sparse point clouds developed an algorithm for reconstructing simplified building models.

**Solar Potential Assessment**

3D city models play a crucial role in estimating a building's sun exposure to assess the suitability of installing solar panels on roofs. These models provide geometric information such as roof tilt, orientation, and area, which serve as essential inputs for solar empirical models (Biljecki, 2015). Jochem et al. (2009) conducted research on automatic roof plane detection using airborne LiDAR point clouds to assess solar potential. Their method achieved roof plane detection with 94.4% completeness and 88.4% correctness, maintaining high accuracy 2. Schuffert et al. (2015) explored using LiDAR and aerial images for quality assessment of roof planes in solar energy systems. The extended quality assessment demonstrated benefits, with completeness values ranging from 87% to 96%, correctness from 83% to 99%, and overall quality from 80% to 92%.

Jochem et al. (2011) investigated using LiDAR data for solar potential assessment, including the extraction of vertical walls from mobile laser scanning. Additionally, Huang et al. (2015) applied GPU-accelerated solar radiation models and airborne LiDAR data to estimate roof solar energy potential in Shanghai. Estimating building insolation is crucial for assessing thermal comfort and identifying buildings exposed to excessive sunlight, which can lead to overheating during summer. Urban layout design can maximize insolation in neighbourhoods, and decentral energy source capacities can be estimated for crisis management applications (Biljecki, 2015). Huang et al. (2017) explored the feasibility of using 3D ground laser scanning point clouds for solar potential assessment, while Mansouri Kouhestani et al. (2019) evaluated rooftop photovoltaic electricity potential using a multi-criteria approach based on GIS and LiDAR systems in Lethbridge, Canada. The city's rooftop PV electricity generation potential was estimated at approximately 38% of its annual consumption.

**Change Detection**

Zu et al. (2015) point out that the detection of changes in the urban environment has become important for land management, the identification of illegal buildings, monitoring urban growth, urban landscape pattern analysis, and updating geographic information databases. Their experimental results have showed that the overall accuracy for change detection of buildings and trees reached 94.8% and 83.8%, respectively. Pang et al. (2014) in their study on building change detection in Guangzhou city, South China used an object-based analysis method using airborne LiDAR data. They found that the proposed method can successfully locate the changed buildings and correctly determine the change type.

In another study, Xu et al. (2015) used point clouds from airborne laser scanning (ALS) data for detecting and classifying changes to buildings. In the study three data sets, located in commercial and residential areas of Rotterdam, the Netherlands have been used. The authors found that their method detected 91% of actual changes in Test area 1(commercial area) and 83% in Test area 2(residential area). Performance analysis has shown that 80%–90% of real changes were found, of which approximately 50% were considered important. Stal et al. (2013) in their study on the application of airborne photogrammetry and LiDAR for DSM extraction and 3D change detection in the inner city of Ghent, Belgium, found that the resulting surface models of both approaches (DSMs generated from both stereo aerial imagery and ASL data) were highly comparable in a qualitative and quantitative/statistical way for various 3D reconstruction of individual buildings or building blocks and other urban features. The techniques have also the potential to be highly complementary in terms of degree of detail, coverage size, the necessity for spectral information, etc. The authors also found that DSM errors, model noise, lack of quality, and insufficient detail or low spatial resolution have a significant impact on the accuracy and performance of the change detection approach.

In another study conducted by Du et al. (2016), aerial images and LiDAR data were used to determine building changes in a test area covering approximately 2.1 $km^2$ and consisting of many different types of buildings. In this experimental study, graph cuts labeling was employed to determine changes, and the height difference was combined with the grey-scale similarity to form the data term of the energy function, and the efficiency of the combined methodology was validated in the experiment. The results indicated that the completeness of more than 93% for positive changes, 94% for negative changes, and correctness of 90.2% and 94.1%, respectively. It can be compared to the building detection result with the same source of multi-temporal data. Recently, Tran et al., (2018) proposed a fusion of automatic classification and change detection based on a supervised machine learning method to detect changes in the objects building and tree, as well as changes of the ground. The results illustrated that the overall accuracy of the classification of each change type of the 2007 dataset and 2015 dataset reached 90.93% and 92.04%, respectively. In their study Shirowzhan et al. (2019) evaluated and compared the performance of five selected algorithms including three pixel-based algorithms, Digital Surface Model differencing (DSMd), Support Vector Machine (SVM) and Maximum Likelihood (ML), and two point-based change detection algorithms (i.e. Cloud to Cloud and Multiple Model to Model Cloud Comparison) for building change detection based on airborne LiDAR point cloud data. The results of the analysis showed that, among point-based algorithms, Multiple Model to Model Cloud Comparison algorithm was able to show the magnitudes of building height changes and differentiate between new and demolished objects.

**Urban Transport**

In their study, Jaakkola et al. (2008) developed retrieval algorithms for road surface modeling using a laser-based mobile mapping system. They successfully identified zebra crossings and curbstones as expected, and correctly classified parking space lines where possible. The mean accuracies achieved were approximately 80% or better for lines, zebra crossings, and curbstones. Additionally, Cabo et al. (2016) applied an algorithm for automatic road asphalt edge delineation from mobile laser scanning (MLS) data. Their method involved transforming the original point cloud into a structured line cloud. By clustering lines based on geometric criteria related to parallelism and proximity, they identified the group containing road lines. An initial road edge polyline was obtained from the end nodes of this group, which was further smoothed using a two-stage filtering process. Testing the algorithm on two datasets from Roamer along a 2.1 km stretch of road yielded similar results: 99% surface correctness (proportion of detected surface within the actual road) and 97% surface completeness (proportion of actual road detected by the algorithm). Combining both datasets increased both completeness and correctness to 98%.

Furthermore, Zhang et al. (2014) explored the use of airborne LiDAR data for automatic vehicle extraction using an object-based point cloud analysis (OBPCA) method. Their approach involved detecting ground points through segmentation-based progressive TIN densification and identifying potential vehicle points based on normalized heights of non-ground points. Subsequently, 3D connected component analysis grouped potential vehicle points into segments, and vehicle segments were detected based on area, rectangularity, and elongatedness. Experimental results demonstrated that their proposed method achieved higher accuracy than the existing mean-shift-based method for vehicle extraction from airborne LiDAR scanning (ALS) point clouds.

Another study by Zhu and Hyyppa (2014) illustrated the possibilities of integrating airborne and mobile laser scanning for 3D modeling of railway environments. The study addressed modeling an entire railway environment, including ground, railroads, buildings, powerlines, pylons, street/traffic lights, and trees, using both MLS and ALS datasets. The authors proposed new solutions for object extraction, 3D reconstruction, model simplification, and final 3D visualization based on image processing technology, 3D randomized Hough transformations (RHT) for planar detection, and a quad-tree approach for ground model simplification.

Additionally, Castro et al. (2015) evaluated the impact of successive station spacing within the vehicle path on sight distance analysis results and the influence of digital terrain model (DTM) resolution. Their findings indicated that DTM resolution significantly affected result quality compared to the distance between calculation points. In recent developments, Jung and Bae (2018) created a near real-time working prototype for road lane detection in complex urban routes using 3D LiDAR data in the cities of Seongnam and Incheon, South Korea. Moreover, Kilani et al. (2021) assessed the potential of an automated method based on LiDAR point cloud data to map and detect road obstacles affecting drivers' field of view at urban intersections. The authors concluded that intersections with limited available sight distances (ASD) posed an increased risk of collisions.

**Flood Inundation Modeling**

A natural phenomenon in the hydrological cycle is flooding. Flooding is necessary to replenish soil fertility by periodically adding nutrients and fine-grained sediment; however, it can also cause loss of life and permanent damage to rural and urban infrastructure (CCRS, ND). Flooding is the most common and damaging natural hazard faced by civilization, and their impact is likely to escalate due to climate change projections, which indicate rising sea levels and more severe cyclonic weather patterns and precipitation (Yang et al., 2011). Topographic data, and more importantly recent and highly accurate LiDAR topographic data, are crucial for flood inundation modeling in the urban environment. Estimating the extent of floods has been a traditional topic in GIS and remote sensing, mostly with digital terrain models. However, modeling of the propagation and impact of flooding by an overflow of water from water bodies or heavy precipitation can be improved by using 3D city models (Biljecki, 2015).

The use of LiDAR data in urban flood modeling is well-documented by Meesuk et al. (2015) who model urban flood by combining top-view LiDAR data with ground-view SfM (structure from motion) observations. The result of their study has shown that the multi-view approach of combining top-view LiDAR data with ground-view SfM observations shows good potential for creating an accurate digital terrain map which can be then used as input for a numerical urban flood model. Ghazali and Kamsin (2008) studied flood hazard in Kuala Lumpur using 3D Computer Graphics and fluid simulation techniques to LIDAR DEM and satellite imagery. They implemented the SPH method using GLU3D to create the water flow in MAYA. They simulated the water using 12,000 particles. First, they tested the particle simulation within the river confluence area. The first testing was inclusive of the first 2 hours of the flash flood incident. The static simulation was based on LIDAR DEM data which they aligned the water level according to time. They created 12000 particles to simulate the water and tested the animation in real-time of 18fps.The authors found that by reducing the particles, less computation was used and the accuracy of the simulation can be enhanced. Their study showed that by using 12000 particles, it could handle a fluid simulation with a range of 10,000m$^2$ by using this approach.

In another study, Jakovljevic et al. (2019) presented a technique of point cloud classification and ground point filtering using deep learning (DL) and Neural networks (NN) algorithms and the results showed that UAV SfM provides a derived DEM with a resolution and accuracy that are suitable for flood risk management. Li et al. (2021) evaluated the potential of UAV platform, LiDAR sensor for flood management and the results demonstrated that LiDAR UAV techniques are an efficient and dependable method for surveying terrain making them highly important for creating high accurate flood simulation. In another study, Gebrehiwot et al. (2021) evaluated and compared two methods for inundation depth estimation based on UAV images and topographic data and; the results showed that deep learning-based method is a promising approach to classify the SFM flood water point cloud and create a 3D water surface.

**Other Applications**

In their study, Yan et al., 2015 highlight the utility of airborne LiDAR data for urban land cover classification. While early studies primarily focused on geometric aspects of 3D LiDAR point clouds, recent interest has shifted toward leveraging intensity data, waveform data, and multi-sensor information to enhance land cover classification and object recognition in urban environments. The authors review and discuss advancements in airborne LiDAR technology, including data configuration, feature spaces, classification techniques, and radiometric calibration/correction. Additionally, Kim (2016) proposes a technique to improve land cover classification accuracy by addressing misclassification of building objects through the fusion of aerial images and airborne LiDAR data. In another study, Zhang et al. (2015) employ LiDAR for automated urban forest inventory at the individual tree level. Giannico et al. (2016) estimates forest stand volume and above-ground biomass (AGB) in urban and peri-urban areas. Rutzinger et al. (2008) also used LiDAR for classifying urban vegetation. Schreyer et al. (2014) model urban tree carbon storage and distribution. Cheng et al. (2014) explore using vehicle-borne LiDAR data to extract urban power lines.

Zhang & Shao (2021) evaluated the feasibility of urban vegetative above ground biomass (AGB) estimation by integrating terrestrial AGB observations and multi-source remote-sensing data and the results demonstrated that the proposed approach improved the inversion accuracy of estimating urban vegetation biomass. In their study

Lafortezza & Giannico (2019) evaluated the potential of integrating of stakeholders' perception with high-resolution satellite images and LiDAR) point-cloud to assess the ecosystem services (ESS) provided by urban green spaces. In another study, Inzerillo et al. (2018) developed a model for road pavement distress analysis using Image-based 3D reconstruction and UAV datasets. The results demonstrated that the proposed integrated method accurately replicates pavement distresses. Balsa-Barreiro & Fritsch (2018) developed a methodology for 3D models of historical cities with the combined use of laser scanning and photogrammetric techniques and the experimental results demonstrated a 3D virtual model with high geometric accuracy.

In recent study, Moretti et al. (2021) explored the application of Geospatial Building Information Modeling (GeoBIM) for assessing the condition of built environments. Their study aimed to enhance decision-making for asset managers by providing location-enabled insights. The authors found that the 3D digital model of a built asset could serve as a valuable component within a broader digital twin of a city. When coupled with real-time sensor devices reporting asset conditions, GeoBIM offers significant potential. Additionally, Jang et al. (2022) proposed a BIM-based management system specifically for Off-Site Construction (OSC) Projects. Their experimental results demonstrated improved efficiency, reduced input time, and decreased workload compared to non-BIM-based management approaches.

## Conclusions and Future Outlook

LiDAR systems are crucially developing and wide-ranging trends are visible in LIDAR applications for 3D city modeling these days. In this context, the main conclusions and outlook of this paper can be summarized as follows:

- Over the past decade there have been an increasing number of examples of LiDAR systems applications in 3D city modeling. 3D city modeling applications of LiDAR include, but are not limited to, building reconstruction, solar power potential assessment, change detection, urban transport system, flood inundation modeling, urban vegetation and urban and peri urban forest, urban land cover classification, urban infrastructure modeling, ecological environment modeling, digital reconstruction, and GeoBIM.
- However, there are still many significant shortcomings related to applications of LiDAR systems including high initial costs and a lack of standardized procedures to process large volumes of data. So far, LiDAR systems have been extensively used for 3D city modeling in the developed world. Unfortunately, many places around the world do not have the resources to obtain LiDAR data. Besides this, the quality of LiDAR products depends upon the sampling and filtering methods used.
- Luckily, it is anticipated that with the advancement of LiDAR technology, lower costs, improved data processing and feature extraction techniques such as handcraft features, segmentation, clustering and deep learning, multisource data fusion and registration, the use of advanced machine learning algorithms and a greater number of experimental studies of laser scanning-based remote

sensing for 3D city modeling applications, there will be a greater expansion of the benefits of this technology for 3D city modeling applications in the developing countries. For instance, the increased availability of LiDAR data at a reasonable cost might make this technique a possible interesting alternative for 3D city modeling, in developing countries like Ethiopia, in their effort for mapping and monitoring of socio-economic, environmental and infrastructure problems in urban areas.

- In fact, LiDAR point cloud data and aerial photography and/or satellite imagery provide complementary information related to 3D city modeling. In this regard, the integration of multisource data such as airborne laser scanning with ground-based laser scanning, air born laser scanning/ground-based laser scanning with aerial photography and/or satellite imagery represents an interesting alternative in 3D city modeling. However, this application is not fully developed, and problems must be solved in order to develop fully integrated applications of LiDAR point cloud data and aerial photography and/or satellite imagery for 3D city modeling. For instance, the problem which needs to be dealt with is advanced algorithms that perform reliably on multi-source LiDAR point cloud and imagery data.
- Another trend accompanying the development of terrestrial and aerial LiDAR systems is intelligent data processing and extraction with state-of-the-art methods such as deep learning. Object recognition and classification from LiDAR point clouds data with newly developed machine learning algorithms will improve reliability of decision support systems and will contribute to modernized 3D object detection, building reconstruction, road safety, disaster risk management and monitoring urban environment, but the need for 3D city modeling using LiDAR point cloud data can be a bit data processing and algorithms extensive. Thus, the increased availability of high quality terrestrial and aerial at reasonable cost such UAV point cloud data and intelligent feature extraction and object reconstruction and classification using the deep learning algorithms makes this technique possible interesting alternative approach for improved point cloud data processing and information retrieval.
- In general, though LiDAR systems cannot capture all types of urban information, they can reliably provide accurate and timely information to socio-economic and environmental, and urban management and monitoring related decision-making.

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