AUTOMATIC GENERATION OF DEM USING SVM CLASSIFIER

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ABSTRACT:

People are moving towards an automated strategy for building a Digital Elevation Model (DEM) from a high-resolution Google Earth photograph as technology advances. Manually terrestrial measurements are both time and money costly. The automatic creation of DEMs became possible because to recent advances in image matching algorithms and intelligent filtering. The goal of this work is to give an overview of how to create DEMs automatically in the tough situation of a build-up area with the extraction of building points. The calculation of building heights, is to produce a digital elevation model, which may be easily obtained by collecting automatic Lidar point cloud data The estimation of building height with its shadow plays important role in determination. In this detection of shadow and removal of false shadow is also very important. During picture segmentation, shadow detection is performed. Statistical features are used to extract the suspected shadow. Support vector machine on IOOPL matching could effectively remove the shadow for shadow removal. The approach can successfully detect shadows in high-resolution remote sensing photos of cities and can effectively repair shadows at a rate of over 95%. SVM classifier with the accuracy of 92% as compared to others on lower end. The average variation in height estimation comes out to be 1.64 m. First, the building with height more than 20 m and slope more than 3 m, give significantly improved precision in determining building height. Second, the strategy is cost-effective because most RS images from Google Earth are free to use with less knowledge of RS is needed for computation.

1. INTRODUCTION

With the development in the LIDAR technology, there has been ease in laser scanning system both in developing countries and in developed countries. LIDAR system is very suitable in generation of digital elevation model and also help in building reconstruction(Charaniya, Manduchi, and Lodha, n.d.). The ground points and non-ground are separated after pre-processing. Following the separation, a DEM can be constructed from these points (ground and non-ground), which are utilised to remove things such as buildings. The need arise for the separation of all lidar point considering the ground points and the non-ground points. DEM Generation and Building Detection from Lidar Data are two regularly used procedures for converting lidar point data into grid structured data. On the lidar grid data, some image processing algorithms and methodologies can be used. Many of the researchers in past have worked over the different set of filters for the ground and non-ground points separation. Habib et al. have worked on morphology filters that are sensitive to error irrespective of the good results. On the other in case of median filter which can be used for decreasing the effect of single error points(Morgan, Habib, and Science 2002). This error can be in different set of patches. The interpolation is based on spatial correlations between nearby points, which are expressed as covariance. A covariance function based on the distance between points is used to calculate the covariance. Furthermore, the removal of non-ground points is done using a weighing system. The weight of point at different locations is determined by the difference between its height and the DEM computed in the previous phase. The DEM interpolation is also affected by the weights.

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The most important aspect of this strategy is obtaining a reasonable estimate of the initial DEM(Sammartano and Spanò 2016). It will be difficult to correct non-ground locations in the initial DEM. The information regarding the height of the building or earth's surface or the estimation can be done with the LIDAR data. Irrespective of the height, the texture can be derived based on the neighbor points, which help in performing the LIDAR data segmentation(Yastikli and Cetin 2017). Slope, variance, and aspect are some examples of texture that can be determined from height data. In the study presented in this publication, two textures were created and utilized to differentiate between the ground and non-ground lidar points. Ground points were used to create the Digital elevation model (DEM), while non-ground points were processed further to extract building zones and establish regular geometric building borders(Affairs et al. 2018). Clement et al. have shown that some of the applications that use LiDAR data. also have showcased the advancement in metrology, cultural heritage which include 3D modelling. Bridge and power line identification, corridor, coastal or opencast mapping, forest management, and change detection are all examples of DTM creation (Demantke et al. 2011; Barbanson et al. 2015). Biljecki vd et al. have shown the ability to create 3D building models in a simple and quick manner has become increasingly significant in recent years(Biljecki, Ledoux, and Stoter 2016). A typical 3D building model is created using a variety of data collecting techniques such as photogrammetry, laser scanning, aperture radar, architectural models, and drawings. Based on the data format employed, algorithms for identifying LiDAR point clouds are divided as: point clouds and raster range images. Bao et al in his study worked directly on LiDAR point clouds, but the second type works with a raster image, necessitating the gridding of the unevenly distributed

LiDAR point cloud. In the second approach, because LiDAR point cloud data is frequently turned into picture data. In this the classic pixel-based classification of objects or object-based segmentation for classification various techniques can be used directly to LiDAR data("IEEE Xplore Full-Text PDF:" n.d.). Many researchers are interested in demonstrating how to gather scale information for structures using celestial geometry and remote sensing satellite images due to the high level of professional abilities and advanced parameters in applying DTM, DSM, and data from various sensors("DTM Generation Process from Airborne LiDAR Data | Download Scientific Diagram" n.d.). This matching method is the most common one that has been studied in recent years. According to Kim et al., Changing the building height until the projected shadows created for an estimated height matching of real shadows(Shruti Bharadwaj et al. 2022). Based on matching function optimization and building height hypothesis, a mono-scope satellite picture is one approach to estimating the height of structures with flat and gable roofs (Wan et al. 2020). Therefore, the authors have to estimation of building height for LIDAR generation the need arises for the algorithm. These algorithms will help in generation of DEM with the help of the google earth images(Dubey et al. 2020).

2. LITERATURE REVIEW

2.1 Extraction of building height

In recent years, GIS-based mapping has grown in popularity, with applications in a variety of fields, as well as in expanding access to geographic data. P.L.N. Raju et al. have estimated the height of the building by extracting using shadow utilizing high-definition satellite images with metadata information(Raju, Chaudhary, and Jha 2014). The extraction of rooftops and shadows, and utilizing Rule-Based approaches, to eliminate the rooftop and shadow region manually/automatically (Comber et al. 2012). After feature extraction, the next step is to estimate the building's height using the Ratio Method and the relationship between sun-satellite geometry to take the rooftop in combination with shadows. According to the results of the performance analysis, the overall mean error of height for the ratio technique is 0.67m, 1.51m for the Example-Based Approach, and 0.96m for the Rule-Based. For height estimation, the manual Ratio Method is the best, but it takes a long time. Because it requires more knowledge and selection of more training samples, as well as slowing down the method's processing rate, the automatic Rule Based Approach is better for height estimation than the Example Based Approach (Raju, Chaudhary, and Jha 2014).

Y. Qian et al. in their study shows the methods for obtaining building height using optical remote sensing images, VHR (Very High Resolution) SAR images, and the fusion of optical and VHR SAR photos are discussed in this study(Çelik et al. 2018). The merits and cons of the three approaches are then summarized. The shadows of buildings are frequently utilized to calculate building height when optical images are available. The precision of this technique varies greatly depending on the algorithms used. In recent years, the supervised classification approach and the edge detection method have become popular(Shruti Bharadwaj and Dubey 2021). Furthermore, volumetric shadow analysis and areal shadow analysis are becoming increasingly common. Wang et al. showcased that computational fluid dynamics (CFD) techniques employed in urban ventilation research (Shahzad et al. 2019). Accurate building data is not always available for CFD investigations(Ai and Mak 2017). The LES of urban ventilation is utilized in this work to evaluate building height extraction from various satellite photos(Brunner, Lemoine, and Bruzzone 2008). Three sets of digital elevation data derived from satellite images in the Mong Kok metropolitan region of Hong Kong are evaluated as a case study. Building height data from optical (stereo) images was of poor quality, which are thought to be more important for pedestrian-level velocity ratios.(Wang and Ng 2018).

The paper describes a method for automatically extracting building heights from monochrome metropolitan images. A volumetric shadow study had already been performed, for retrieving 3D building information such as height, shape, and footprint placement, as well as dealing with hidden building footprints or shadows, the VSA technique was presented (Warth et al. 2019). Manually modifying building heights until projected shadows made for a predicted height and real shadows in the image matched was used to compute building heights. Researchers present an innovative approach for automatic building height extraction based on the VSA in this article(Lee and Kim 2013). This is accomplished by monitoring the position change of projected shadow lines. The goal of this research is to see if, in urban scale seismic performance assessment studies, construction periods can be calculated in relation to building heights using data from unmanned aerial vehicles (UAVs)(Shao, Taff, and Walsh 2011). A small area in the city center of Eskisehir (Turkey) was chosen for this purpose, which includes eight residential reinforced concrete buildings. This study looked into data to obtain building heights for use in calculating building periods. Building heights obtained from UAV data can be used in building period estimation in urban scale assessments (Yastikli and Cetin 2017).

2.2 Generation of DEM

A digital elevation model (DEM) may be utilised in a variety of ways in GIS and CAD. It's the most basic model for making three-dimensional landscape elements. In general, there are two approaches for creating DEM. One is based on a discrete point digital terrain model and is characterised by high speed and low precision(S. Bharadwaj et al. 2020). The other is based on a triangular digital terrain model, and the technology is characterised by moderate speed and great precision. This study presents an algorithm for producing DEM using discrete points that combines the benefits of the two techniques. This approach may generate a triangle that includes the interpolating point while interpolating elevation, and the elevation of the interpolating point can be derived from the triangle(Sefercik et al. 2014).

The use of all types of Digital Elevation Models has improved in recent years. The LiDAR (Light Detection and Ranging) technology, which is based on scanning the terrain using aerial laser telemeters, enables for the quick creation of digital Surface Models (DSM) via simple data interpolation(Comert and Kaplan 2018).

In the study, area is initially separated into three slope classes: (a) zero to five degrees, (b) six to ten degrees, and (c) eleven to fifteen degrees. Second, three different interpolation methods are used to assess each slope class: (a) Inverse Distance Weighting (IDW) (b) Kriging, and (c) Spline are three types of inverse distance weighting. Following that, field survey tachymetry data is used to check accuracy. Use n and 0.760 m for a spatial resolution of 1 m. Initially, the research area is separated into three slope classes: with variation in degree of 0 to 5, 6 to 10, and 11 to 15. Second, three different interpolation algorithms are used to evaluate each slope class: (a) Kriging, (b) Inverse Distance Weighting (IDW), and (c) spline for data interpolation(Dubey et al. 2021). Following that, field survey tachymetry data is used to assess accuracy (Comert and Kaplan 2018).

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3. RESEARCH GAP

Earlier in the researches author found that in the primitive technique for collecting the data requirement of measuring instrument like total station, GPS, measuring tape was required and the technique has its disadvantage of low accuracy due to manpower inculcated. Also, in the primitive technique of data collection for generating Lidar data was time consuming and need lot of manpower. For 3D modelling requires point cloud data. an algorithm is needed for the extraction of features from 3D point cloud data. The 3D mapping requires the Lidar data, modelled data, building-points. These points were extracted or calculated with the help of algorithms. Lidar data is collected using TLS, but it requires time and manpower so for automation. The generation of data is to be automated which requires building corner details that can be retrieved from the google earth image. The attenuation due to these points by extracting the building height were précised but time consuming. In cased of manual interference the need arises for the automatic generation of Lidar data for creating the DEM. The main target is to make the noise map of road noise by automation. The objective is data acquisition which is fulfilled by collecting the data. The noise data is to be represented by creating the DEM to showcase the effect of noise over the buildings.

4. OBJECTIVES

The authors of this study aimed to determine the height of the buildings and later generation of DEM with the LIDAR for creating 3D noise map.

1. To extract the features from the google images.
2. With the help of the shadow, estimate the height of the building for 3D mapping.
3. To generate the DEM automatically with the help of the created LIDAR data for creating noise map.

5. METHODOLOGY

The RGIPT's project area as seen on Google Earth. Some tests should be carried out in order to readily utilise images from Google Earth. For example, in order to obtain information about shadow height and building height, the authors have first classified shadow and building from the Google Earth image. This classification is performed using various classifiers. The one having the higher accuracy for the selected project area is selected. After that, the height of a certain building is calculated using Google Earth's geometry and data collecting tool. The annotation is used to train the data. The data is trained on the basis of the colour and shape of the features. Then the testing is being performed over other data set. The height of neighbouring buildings in the project area will now be calculated using the ratio of building to shadow length. Following the calculation of building heights, the goal now is to produce a digital elevation model, which may be easily obtained by collecting automatic Lidar data. This is being performed for the RGIPT campus having uniformed buildings structure as shown in the figure. From the estimation of height of building the height of neighbouring building is calculated using the reference frame of main building. 3D point cloud data containing feature information such as trees, buildings, and other objects is required for the creation of a DEM. The DEM is creating using the point cloud data. Authors solely classify and retrieve building height in order to create 3D point cloud data that only contains building data. From the building height and building coordinates acquired from a Google Earth image, an algorithm is built to construct 3D point cloud data. The DEM can be built in Arc Scene once the 3D point cloud data has been obtained.

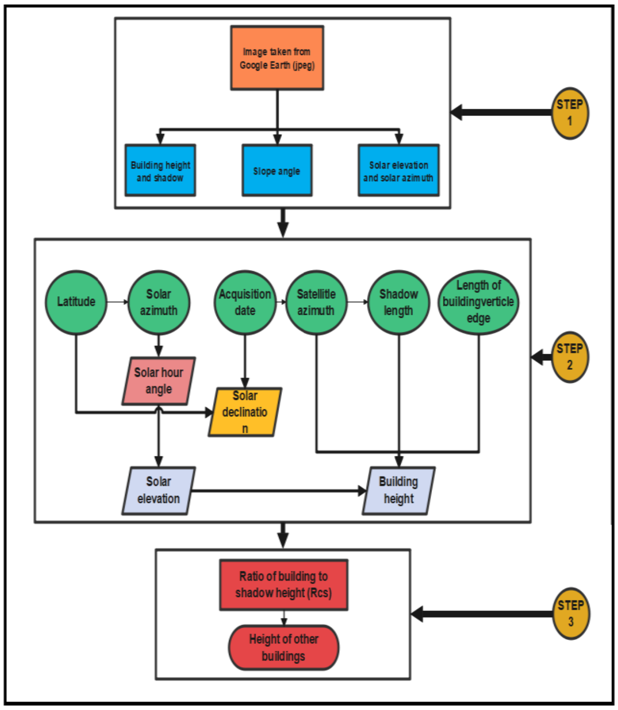

Figure 1. Flowchart of building height estimation

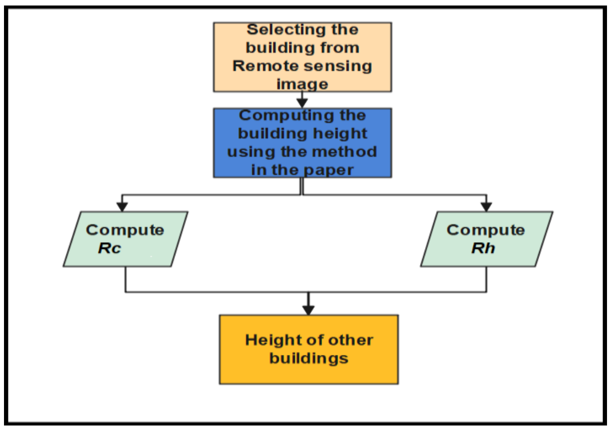

Figure 2. Height estimation of other building with the calculation made for main building.

Figure.3. RGIPT google image with shadow of each building

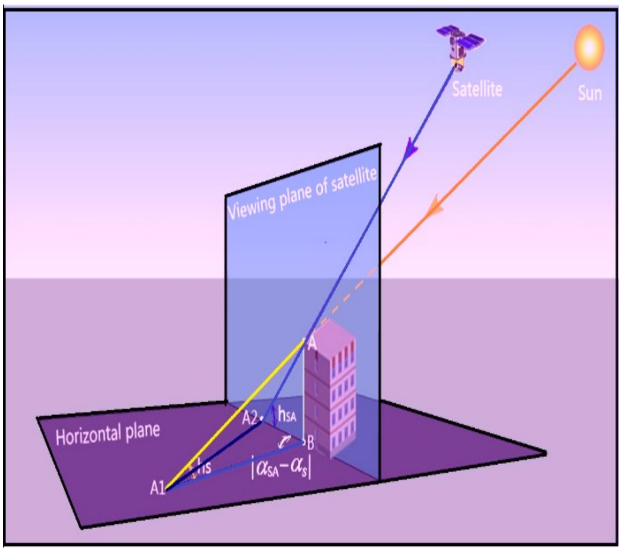

Figure. 4. Relationship between building and shadow.

6. RESULTS

The flowchart in figure 5 shows the flowchart of SVM classifier. The image can be classified by segmenting it and deleting the false shadow to retrieve the original shadow for determing the height of the building. In this the histogram is created from the inner and outer lines generation considering the IOOPL and IOOPL matching.

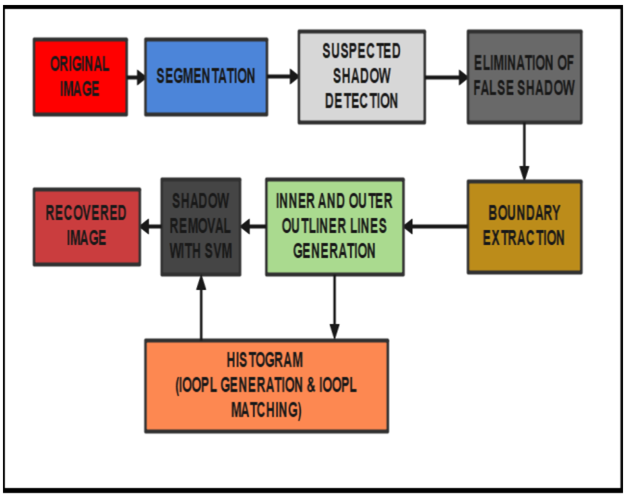

Figure 5. Flowchart of SVM classifier.

The image of the projected area of RGIPT is classified using the above SVM classifier. In this the figure 2(d) shows the classified image which is being retrieved out with the shadow. This shadow help in estimation of height of other buildings.

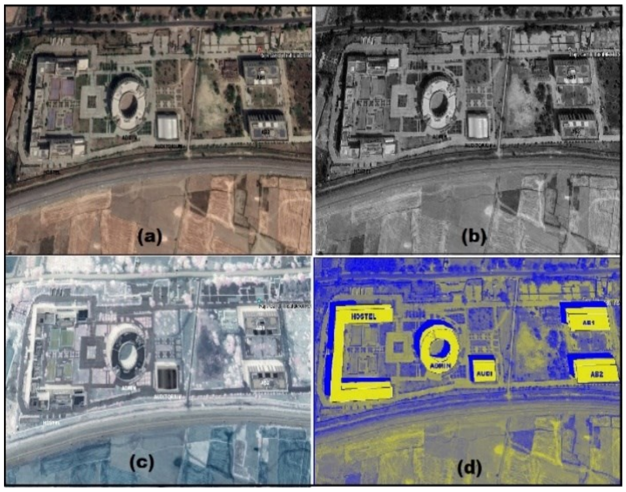

Figure 6. Image classification using SVM. (a) original image of RGIPT, (b) Grey scale image of RGIPT, (c) shadow retrieving of RGIPT, (d) classified image of RGIPT

The histogram of the classified image is being made for the RGIPT area in grey scale and RGB shows in figure 7.

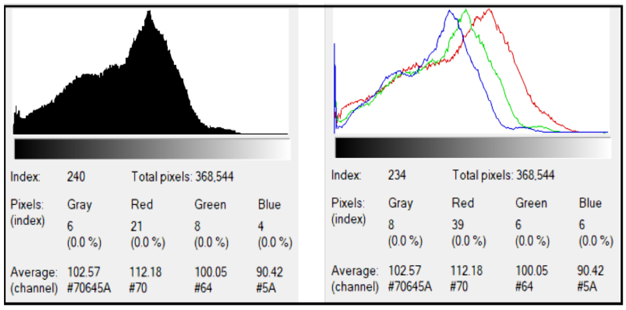

Figure 7. Histogram of RGIPT (grey scale and RGB)

The height of the building of RGIPT is being determined showing the image with the shadow width.

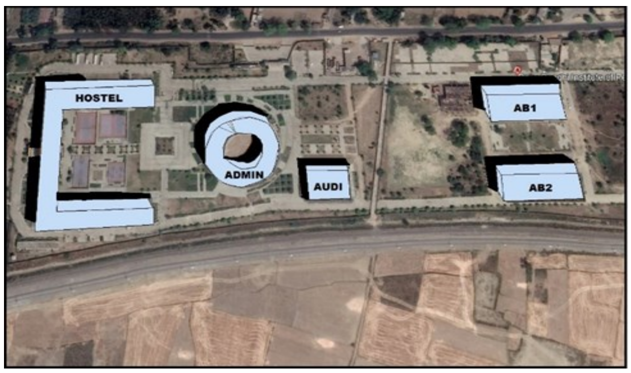

Figure 8. RGIPT building with shadow for height calculation.

Various classifier has been tested for the location RGIPT and the one with the best accuracy for the projected area is being considered for image classification is shown in figure 1.

Table 1. Image classifier accuracy for classification of RGIPT image

S.No.	classifier	Accuracy	percentage
1	SVM	0.92	92

2	NAIVES	0.76	76
3	Random forest	0.85	85
4	Traditional method	0.69	69

Traditional method of image classification with the digital number in figure 9.

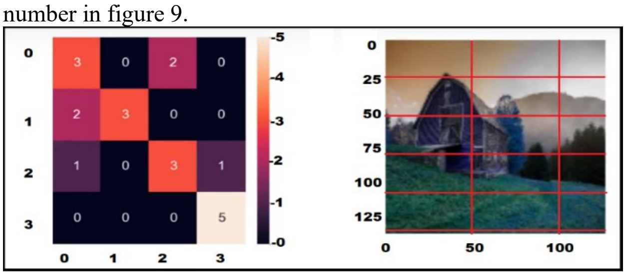

Figure 9. Traditional image classifier

The algorithm helps in determining the building height and shadow height. The average variation in the actual height and the calculated height of the building is being showed in the table 2. for RGIPT.

Table 2. Building height and shadow height estimation with SVM.

S.No.	Building	Shadow height	Height	Actual height	Difference
1	Admin	33.21	28.85	30	1.15
2	AB1	34.24	29.13	30	0.87
3	AB2	32	30.08	30	0.08
4	Hostel	28.11	25.69	30	4.31
5	Audi	14.26	13.19	15	1.81
				Average	**1.644**

The extracted building height and its shadow with precision and accuracy is being shown.

Table 3. SVM classifier accuracy, precision and recall for all features

SVM	ROAD	BUILDING	VEGETATION	SHADOW
Accuracy	0.82	0.88	0.88	0.90
Precision	0.77	0.70	0.68	0.85
Recall	0.86	0.93	0.91	0.92

For the generation of the DEM, with the help of extracted height using the generated Lidar data for 3D point cloud is being shown in figure 10. The algorithm for generating the 3D point cloud data for DEM generation automatically over the Arc Scene is shown

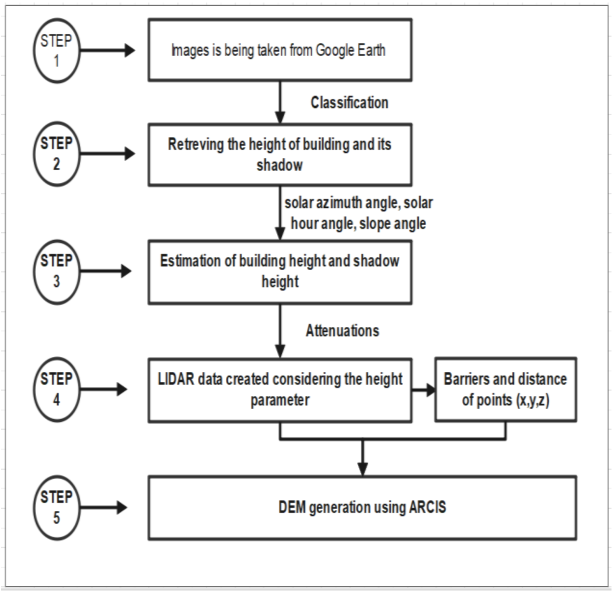

Figure 10. Flowchart of algorithm for generation of DEM

For the projected area RGIPT in figure 11 and figure 12. Tin is being created automatically with the help of the lidar data and later the DEM is being created over with the model data can be inculcated.

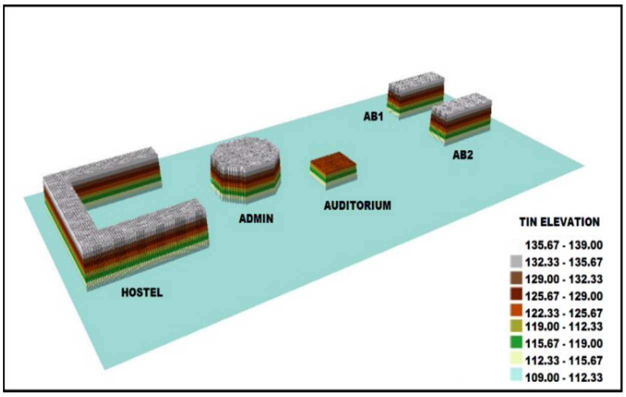

Figure 11. Tin for the LIDAR generated data of RGIPT using the algorithm.

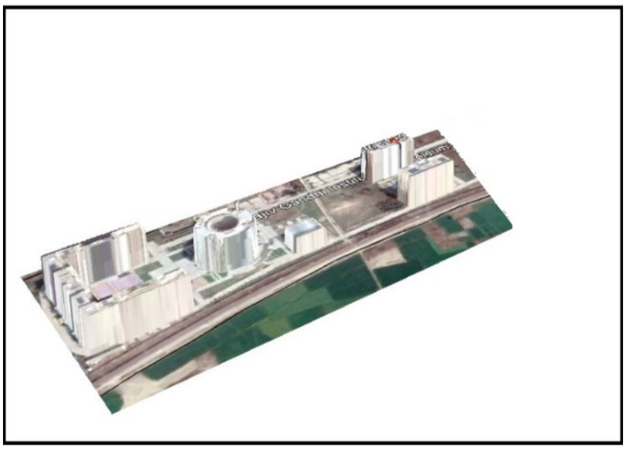

Figure 12. TIN of RGIPT with DEM of RGIPT

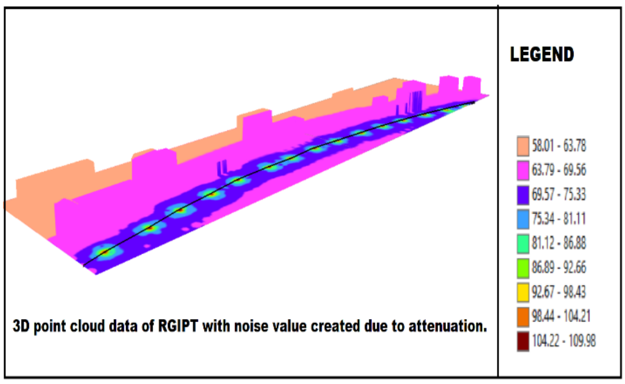

Figure 13. 3D noise map of RGIPT with train noise being the source.

6. CONCLUSION

The authors reviewed at the work of a number of researchers who were working on creating 3D point cloud data using Lidar data. The challenge of generating the Lidar data using the primitive technique was time consuming, require manpower and was cost expensive. Handling such data was also constraint. As the data collected has to be processed and inculcating the algorithm to determine the individual height building and feature extraction. In order to reduce such constraints, the authors have developed an algorithm in which image from the google earth is taken and with the help of SVM classifier having higher accuracy of 92 % for the selected project area RGIPT with the help of known building height and shadow, determine the height of other buildings. This determination of building height help in creating the 3D point cloud data for creating the DEM. This technique reduces the logistic constraints. Also, this technique can be used in traffic road noise control. With the help of google earth image and analysing the image acquisitions to generate the noise map of the road. The SVM was best for the selected location or the location with same type of attributes. The average variation in the height estimated and actual height comes out to be 1.64m. Further in future authors increase the data base then other classifier will also help in determination with better accuracy.

7. FUTURE SCOPE

In the present work the authors have classified only the building and shadow for determination of building height. Only the building and its shadow information are included in the 3D point cloud data that is being created. The classification is only being done for the project area RGIPT. In future work tree, vegetation, road and others 3D point cloud data can be retrieved. This will help in creation of DEM with precision and accuracy. Various algorithms can also be generated for creating the point cloud data if the height can be retrieved for the features like building road, tress etc. the modelled data over this created DEM help in showcasing the noise due to road traffic and other sources. The analysing over such huge data can easily be processed with better accuracy and precision.

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