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Potential analyses of LiDAR-based automatic powerline detection algorithms

Mertcan Nazar*[1], Umut Gunes Sefercik [1], Ilyas Aydın [1]

[1]*Gebze Technical University, Department of Geomatics Engineering, Türkiye, mnazar@gtu.edu.tr; sefercik@gtu.edu.tr; ilyasaydin@gtu.edu.tr*

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Abstract

Powerlines are utilized for distributing electricity for household use, industry, healthcare purposes and etc. The detection of powerlines is an important topic in object detection studies. In addition, overgrown trees in dense forest regions may pose a risk for powerlines positioned in these regions and even may cause forest fires if unattended. So, it is also important in the scope of disaster monitoring research and studies. Light detection and ranging (LiDAR) systems are utilized for the detection of powerlines in urban regions and forests with the ability to obtain high-resolution point cloud data. Also, with the operation principle based on active remote sensing aerial LiDAR systems with multi-return capability can be used to obtain information about forest understory and is more effective compared to optical systems in this context. In this study, aerial LiDAR point cloud data of an urban region was utilized for the automatic detection of powerlines. For the automatic detection of powerlines, Robust Railroad Infrastructure Detection Framework which was developed by Eötvös Loránd University (ELTE) Geoinformatics Laboratory was utilized and five algorithms including Above, AngleAbove, AngleGroundAbove, VoronoiAbove, and VoronoiGroundAbove are applied separately on LiDAR point cloud data. When results are analyzed visually AngleAbove gave the best results in powerline detection.

Introduction

Powerlines are utilized in the distribution of electricity in towns, cities, and countries for general household usage, industrial requirements, healthcare, agriculture, etc. However, rapid urbanization and overgrowth in forests can pose a significant risk for powerlines in urban and rural regions. Also, sudden changes in wind speeds can cause powerline induced fires in wildlands due to the ignition of broken lines by contact with trees [1]. So, the inspection of powerlines especially in high-risk regions is an important topic in the scope of disaster monitoring. Presently, powerline corridor management in forest regions primarily consists of detecting and trimming trees with high risk which could fall and cause damage to the structure, and using conventional men-centric monitoring methods is time-consuming, includes high cost, and is a hazardous work process [2]. However, instead of using the conventional powerline monitoring method airborne light detection and ranging (LiDAR) technique which has the ability to generate densely populated three-dimensional (3D) point clouds in a short time and with less cost, can be utilized in powerline detection. Moreover, utilizing airborne LiDAR point clouds high-quality digital surface models (DSM) can be produced with high geolocation accuracy [3-4]. LiDAR systems are utilized in disaster monitoring studies such as detecting the spatial distribution of wildland fuel types and properties for forest fire management, observing characteristics of aerosol particles that emerged as a result of volcanic eruptions using LiDAR measurements, estimation of 3D coseismic displacement after earthquake and detection of collapsed buildings due to earthquake from LiDAR DSM and automated power line extraction from airborne LiDAR point cloud in forest areas [5-8]. In this study, Robust Railroad Infrastructure Detection Framework which was developed by Eötvös Loránd University (ELTE) Geoinformatics Laboratory was used for the automatic detection of powerlines in an aerial LiDAR point cloud. Five algorithms namely Above, AngleAbove, AngleGroundAbove, VoronoiAbove, and VoronoiGroundAbove are applied individually on point cloud data to see the results of different detection algorithms and to determine which performs better when analyzed visually.

Material and Method

A point cloud which was obtained by aerial LiDAR surveys was utilized for the automatic detection of powerlines in an urban area where there are different land cover classes including powerlines, buildings, roads, and vegetation. Point cloud data was large in size so for the test study it was scaled down to a strip with a length of approx. 1.25 km and a point number of nearly 3.8 million (Figure 1).

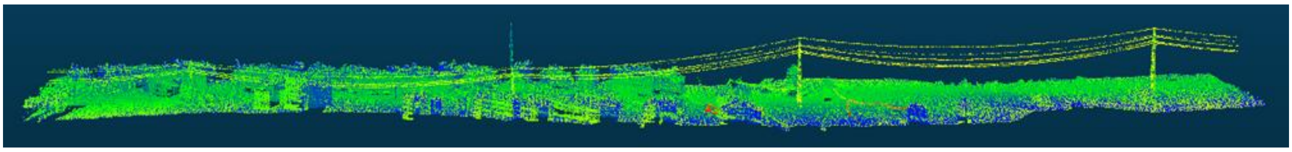

Figure 1. LiDAR point cloud of the study area

For the automatic detection of powerlines in the study area Robust Railroad Infrastructure Detection Framework which is a software library and a tool for automatic rail track and cable detection from LiDAR point clouds, was utilized. The automatic detection tool includes filtering algorithms for reducing the size of the point cloud and projection filters for generating a two-dimensional projection of the original 3D point cloud to minimize the computational load during the detection process [9]. Five algorithms such as Above, AngleAbove, AngleGroundAbove, VoronoiAbove, and VoronoiGroundAbove are applied separately on point cloud data. Applying these algorithms, a probabilistic Hough line detection algorithm is applied after the projection phase. The probabilistic Hough transform is given in Equation (1) [10].

$$H(\vec{y}) = \sum_{i=1}^{n} \ln[f(\vec{x}_i|\vec{y})] + \ln[f_0] + C \quad (1)$$

Where n is the number of input features, $\vec{x}_i$ is a specific image measurement, $\vec{y}$ is a specific point in Hough space, $f(\vec{x}_i|\vec{y})$ is the probability density function of $\vec{x}_i$ given the value of $\vec{y}$, f_0 a priori probability density function and C is the arbitrary constant.

Results

The results of the applied detection algorithms are presented in Figure 2.

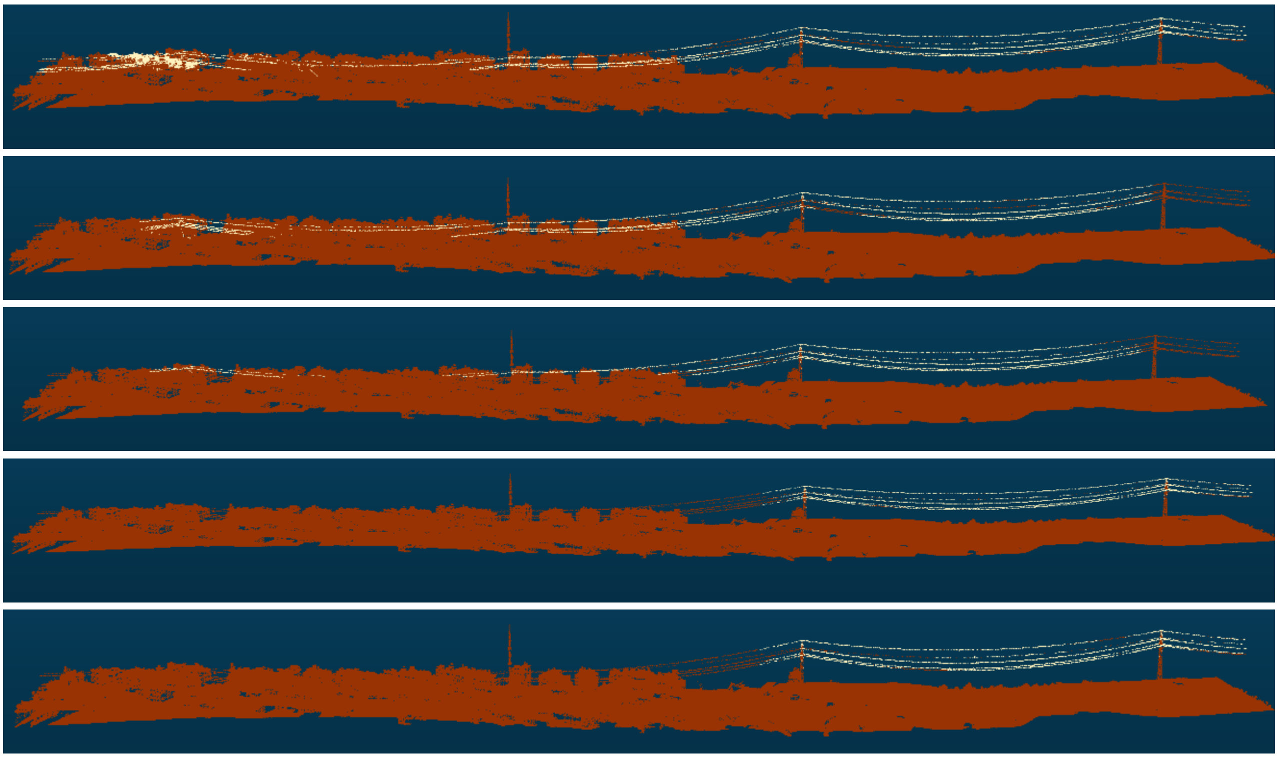

Figure 2. Results of the applied detection algorithms Above (a), AngleAbove (b), AngleGroundAbove (c), VoronoiAbove (d), and VoronoiGroundAbove (e). Detected powerline points are in yellow color.

When the results are visually analyzed AngleAbove algorithm performed better compared to other detection algorithms. VoronoiAbove and VoronoiGroundAbove algorithms performed worse than other ones whilst detecting only a limited number of powerline points. Above and AngleAbove algorithms gave similar results while the Above algorithm incorrectly detected other object points as powerline points compared to AngleAbove. AngleGroundAbove gave average results between other algorithms. In parts of the point cloud where points of other land cover classes including buildings, and vegetation are existing, the performance of detection algorithms was decreased.

Conclusion

Various disaster monitoring studies are carried out using LiDAR systems and the results obtained can be used by decision makers in disaster prevention and post-disaster recovery and rehabilitation. It has been observed that the AngleAbove detection algorithm, which is applied within the scope of the Robust Railroad Infrastructure Detection Framework for the detection of powerlines, has a higher success in visual analysis compared to other algorithms. It has been observed that detection algorithms give different results depending on the topography and object structure. It is understood that detection algorithms give different results depending on the topography and object structure.

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