MANAGING POWER INFRASTRUCTURE USING LIDAR

Vivian Sultan, PhD California State University, Los Angeles College of Business & Economics Email: vsultan3@calstatela.edu



ABOUT VIVIAN SULTAN

Professor of Information Systems and Business Management at California State University (CSULA). Dr. Sultan holds a PhD in Information Systems and Technology from Claremont Graduate University. She is a certified professional in Supply Management with demonstrated expertise in account product management, operations, and automated system projects development. Prior to her current role, Dr. Sultan served as a Senior Analyst at Southern California Edison, an Account Product Manager at the Walt Disney Studios. Her publications and research focus on energy informatics and the digital transformation within supply chains



BACKGROUND ON THE ISSUE AT HAND

- Utility companies are expected to increase energy production to keep up with demand
- Utility companies are also experiencing heightened regulatory scrutiny and standards to maintain their grid equipment
- Collecting LiDAR data through UAVs is a cost-efficient alternative to sending out teams on the ground to inspect assets (power poles and towers)

Unmanned Aerial Vehicle (UAV)



IMAGE SOURCE: AZEVEDO, F., ET AL. (2019)

LIDAR DATA

3D aerial scan of a location that will be used in Geographical Information Systems to classify buildings, trees, or any other point of interest depending on research.

Finished Product Showing Processed Data



IMAGE SOURCE: AZEVEDO, F., ET AL. (2019)

CONTEXT & RESEARCH QUESTION

Condensed Scope Statement

Due to market landscape changes that increased regulatory requirements and heightened regulatory scrutiny of utility companies, cost-efficient alternatives to manage assets must be examined. LiDAR data is a tool that can potentially help power companies manage their equipment inventory.



VAN LEEUWEN, M., & NIEUWENHUIS, M. (2010)

- Discusses how remote sensing techniques can help identify objects
- Indicates that future research involving machine learning should be investigated

AZEVEDO, F., ET AL (2019)

- Examines usage of unmanned aerial vehicles (UAVs) to map out the power lines and power grids
- Summarizes Point Cloud Segmentation (PCS), the process of classifying points, and how that can be used to take pictures of power grids

NAHHAS, F., ET AL (2018)

 Using machine learning with LiDAR data helps map out structures using machine learning to differentiate Point Cloud Data

PREVIOUS RESEARCH

CONDUCTED

 Spectral imagery and orthophotos can be used to help differentiate buildings from their surroundings

KUDINOV, D. (2019)

 Utilized deep learning and the Point Convolution Neural Network (Point CNN) framework to identify power lines and power poles in a LiDAR point cloud dataset

DATA SOURCES

• United States Geological Survey (USGS)



DATA

Point cloud data covering a region in Santa Cruz,
 West Hollywood, and North Long Beach were
 downloaded and analysed

Region	File Size	Points
North Long Beach	1.52GB	54,586,808
Santa Cruz	3.20GB	94,505,117
West Hollywood	1.57GB	32,233,675

TOOLS & RESOURCES

OARCGIS PRO 2.8

OARCGIS SATELLITE IMAGERY

• MACHINE LEARNING MODEL FROM ARCGIS ONLINE

• USAGE OF CUDA AND COMPUTE UNITS TO INCREASE PROCESSING SPEED FOR MACHINE LEARNING

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APPROACH

- Instantiated the use of an existing model to the areas of interest
- Utilized a geoprocessing tool known as "Classify Point Cloud Using Trained Model" and leverage a trained model to extract power poles
- Explored the application of the model in both rural and urban areas to assess the performance of the model
- Explored performance of the model with varying levels of classification intensity



- The deep learning model technically achieved its objective as it was successful at correctly classifying points as power poles and towers
- The performance was not overwhelming, it is still a work in progress tool
- The deep learning model did not classify any points in the denser forest areas of Santa Cruz, CA.

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IMAGES OF THE FINAL RESULTS





Long Beach, CA

Scotts Valley, CA (Santa Cruz County)



IMAGES OF THE FINAL RESULTS





DOWNLOADING DATA

- Step 1: Navigate to the national map found on the USGS website, available at: https://prd-tnm.s3.amazonaws.com/LidarExplorer/index.html#/.
- Step 2: Select "show where Lidar is available" and "Show AOI Results".
- Step 3: Select the area of interest.
- Step 4. Download the LiDAR data provided for the area of interest.



CONVERTING LAZ TO LAS

- Step 1: Download a publicly available conversion tool available at: <u>http://lastools.org/download/laszip.exe</u>. Place the downloaded file tool in the folder where your LAZ files are located.
- Step 2: Search for the Command Prompt in the search menu, then press CRTL + Shift + Enter. The computer will ask if the user would like to allow the application to make changes to their computer. Select YES.
- Type **cd /d** and then copy the file location, and add the following extension: laszip.exe *.laz



• When the files are done converting they will appear in the folder where the Laz files were located.

DOWNLOAD DEEPLEARNING FRAMEWORK & MODEL

- Step 1: Download and install required tools to run deep learning models on ArcGIS, available at: <u>https://github.com/Esri/deep-learning-frameworks/blob/master/README.md?rmedium=links_esri_com_b_d&rsource=https%3A%2F%2Flinks.esri.com%2Fdeep-learning-framework-install
 </u>
- Step 2: Download the deep learning model to classify power lines, available at: <u>https://www.arcgis.com/home/item.html?id=6ce6dae2d62c4037afc3a3abd19afb11</u>. You can also find the tool on ArcGIS online, accessible through the ArcGIS Catalog Pane.



Power Line Classification		Overview
	Deep learning model to classify point clouds into distribution wires, poles, or background. Deep Learning Package by esri_enalytica Created: Dec 15.2020 Updated: Jul 12.2021 Number of Downloads: 895 Q Living Atlas	Dawnload
Description		
	d datasets to identify distribution wires is useful for identifying vegetation encroachment around power ortant for preventing fires and power outages and are typically manual, recurring, and labor-intensive.	Details Size: 13 MB
with changes in geography as	act distribution wires at the street level. Its predictions for high-tension transmission wires are less consistent compared to street-level distribution wires. In the case of high-tension transmission wires, a lower 'recall' d to the value observed for low-lying street wires and poles.	T ¥ 3
Licensing requirements		Share
ArcGIS Desktop - ArcGIS 3D A	nalyst extension for ArcGIS Pro	Ø
	the supported deep learning libraries are installed. For more details, check Deep Learning Libraries I can be used with ArcGIS Pro's Classify Point Cloud Using Trained Model tool. Follow the guide here to use	Owner
Note: Deep learning is compu	tationally intensive, and a powerful GPU is recommended to process large datasets.	Tags
Input	d point clouds with point geometry (X, Y and Z values).	dlpk, power line detection, power lines, deep learning, vegetation enroschment, machine

CREATE LAS DATASET & CONVERT COORDINATES

- Step 1: Navigate to the Geoprocessing Tools pane in ArcGIS Pro. Search for Create LAS Dataset. Click on the folder icon under Input Files and locate the LAS files to import. Under Create PRJ For LAS Files, select All LAS Files. Click on the globe icon under Coordinate System. A separate window will open as shown below where coordinate systems can be changed.
- Step 2: Click on Current XY and navigate to the NAD 1983 NSRS2007 California (Teale) Albers (Meters). It is found by expanding Projected Coordinate System --> State Systems
- Step 3: Click on Current Z and navigate to NAD 1983 (NSRS2007). It can be found by expanding Vertical Coordinate System à Ellipsoidal based --> North America. Once the XY and Z coordinates are correctly specified, click OK.

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RUN CLASSIFY POINT CLOUD WITH TRAINED MODEL

- Step 1: Open the Classify Point Cloud With Trained Model geoprocessing tool.
- Step 2: Enter your LAS data set under *Target Point Cloud*. Under Input Model Definition, locate the deep learning model to classify power lines by clicking on the folder icon and retrieving the file. Under *Existing Class Code Heading*, select Edit Selected Points. Under *Existing Class Codes*, select "1". After all parameters have been entered, click Run. The required time to complete depends upon the size of the data set. At a minimum, one can expect the model to take 4 hours to complete.
- Step 3: Filter the layer to display only power poles:

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DISCUSSION OF FINDINGS AND NEXT STEPS

 The point cloud data utilized in this project may not share characteristics present in the data used to train the employed deep learning model

NEXT STEPS

• Prepare point cloud data with accurately labeled power poles and towers and

that are a good representation of the objects of interest to train a model

- Prepare validation data
- Train model
- Utilize model

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Appendix A

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THANK YOU!