Fine-Grained Distribution Grid Mapping Using Street View Imagery

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Abstract

Fine-grained distribution grid mapping is essential for power system operation and planning in the aspects of renewable energy integration, vegetation management, and risk assessment. However, currently such information can be inaccurate, outdated, or incomplete. Existing grid topology reconstruction methods heavily rely on various assumptions and measurement data that is not widely available. To bridge this gap, we propose a machine-learning-based method that automatically detects, localizes, and estimates the interconnection of distribution power lines and utility poles using readily-available street views in the *upward* perspective. We demonstrate the superior image-level and region-level accuracy of our method on a real-world distribution grid test case.

1 Introduction

Distributed Energy Resources (DERs) such as photovoltaic (PV) and wind power generators are widely adopted at an unprecedented pace. For example, the cumulative global PV capacity is estimated to be 500GW in 2018 with a 20% annual increment, and projected to be over 1100GW in 2023 [1]. While these DERs play an increasingly important role in decarbonizing the energy sector and addressing climate change, their deep penetration into the power systems poses significant challenge on grid stability and resilience due to the bidirectional power flow they create. Integration of DERs to the power grids requires the detailed knowledge of the grid connectivity, especially that of distribution grid. However, unlike transmission networks whose connectivities are well documented, the topology information of distribution grid can be outdated, inaccurate, and even unavailable due to frequent grid reconfiguration and poor knowledge on the connectivity of privately-owned DERs. OpenStreetMap [2] collects the geolocation information of power lines and utility poles using crowdsourcing method yet it is far from complete. Existing works on distribution grid topology reconstruction heavily rely on various assumptions and data availability, such as radial topology assumption [3, 4] and the availability of smart meter time-series data [5, 6, 7]. However, many distribution networks in the real world contain meshed structures, and smart meters are not widely deployed around the world. Even in the U.S, the penetration rate of smart meters is less than 50% [8], and their data are owned by different private companies. Such bottlenecks limit the feasibility and scalability of these methods and make them difficult to validate on real-world distribution networks.

The breakthrough of deep learning techniques [9] and the availability of widespread and frequently-updated street view imagery provide an alternative approach for fine-grained infrastructure mapping. [10] introduced a pipeline that uses fully convolutional neural networks (FCNN) to segment the regions of telegraph poles in street views, estimates their distance from the camera, and localizes them with triangulation. [11] used a fully-supervised object detection model to detect utility poles in images, and estimate their geolocations with a simple cross bearing algorithm without the need of monocular depth estimation. However, neither of them has detected power lines from the street views

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and used them to connect poles for a complete distribution grid map. Besides, they both relied on fully-supervised detection or segmentation methods requiring large number of bounding boxes or boundary annotations for training. In contrast, we propose a semi-supervised learning framework requiring only image-level labels to detect and localize both distribution lines and utility poles in street views towards a complete and granular distribution grid mapping. We evaluate our model on a real-world distribution grid map in California. Besides the usage in distribution grid topology reconstruction, grid mapping produced by our method can be further combined with tree location map, renewable generation inventory, and weather data to facilitate various power system stakeholders in the aspects of vegetation management, DER integration, risk assessment, and disaster prevention.

2 Methods

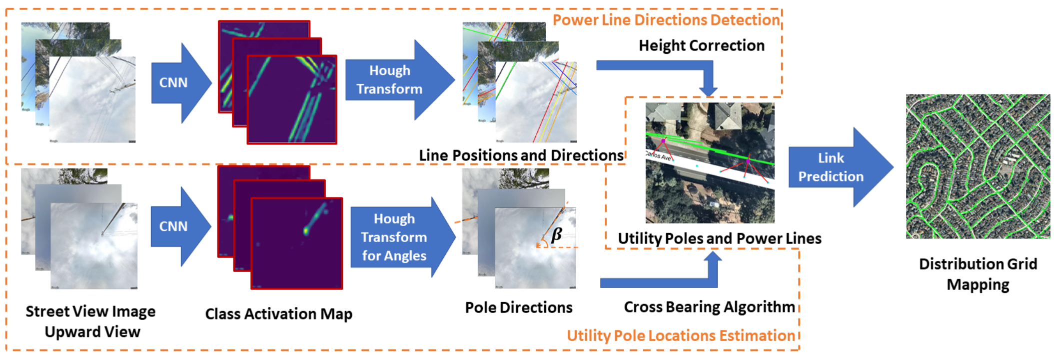

Figure 1: Proposed framework, which consists of power line detection module and utility pole detection module. Pole detection is only applied on images in which line has been detected.

Figure 1 shows the model framework which is comprised of two modules: (1) A power line detection module that takes upward street view image as input and outputs the line positions and directions if and only if the input is classified to contain line(s). (2) A utility pole detection module that takes upward street view image as input and outputs the bearing of the pole within the image if and only if the input is classified to contain pole(s). Based on the assumption that *a utility pole must be accompanied by power lines in an upward street view but not vice versa*, we apply pole detection module *only* on images that are classified to contain line(s) to reduce false positive pole detection. Such assumption is based on the observation of our dataset. Finally, we generate the distribution grid map by attaching lines to their nearby poles based on geolocations and line directions.

Upward view. In contrast to previous works [10, 11] that used horizontal or near-horizontal perspective of street views to localize objects, we choose the upward view as model inputs which has rarely been proposed in existing literature on street view object recognition. This is because there are much fewer irrelevant objects in the upward view compared to horizontal view, while utility poles and power lines near the streets are sufficiently high to be captured in images. Furthermore, we set the street view heading consistently to 0 when retrieving images. Such specifications significantly simplify the geometric relationships of power lines and utility poles in images, and thus facilitate the direction estimation and localization.

Power line detection module. Training fully-supervised object detection models needs large datasets with detailed bounding box annotations, which can be expensive and time-consuming to obtain. Instead, we use a semi-supervised model to generate the activated regions of power lines in an image requiring only image-level binary label indicating whether it contains line ("positive") or not ("negative"). We adopt the training scheme proposed in [12] (Appendix A.3). Specifically, we firstly train a classification model to classify whether an image is positive or negative using the Inception-v3 architecture [13]. Then we add an additional CNN branch directly connected to an intermediate layer of the classifier and further train it for classification while keeping the main branch fixed. We use this branch to produce Class Activation Map (CAM) [14] that highlights line regions. Note that CAM is generated only if the classification result is "positive". We estimate the line directions in CAMs using Hough transform (See details in Appendix A.1). Due to the geometric simplicity of upward views, the direction detected in an image is exactly the actual line direction on maps.

Utility pole detection module. We use the same CNN architecture in the line detection module to detect utility poles in input images and generate CAMs for positive detections. To localize poles on the map, we assume *all utility poles are completely vertical cylinders.* In this way, any pole appearing in an *upward* street view must point to the image center, and the bearing of pole can be derived by calculating the angle between the pole and horizontal axis in the image (β in Figure 1). We use another Hough transform to implement this process (Details in Appendix A.2). Finally, by intersecting the line-of-bearings (LOBs) derived from at least 2 view points and clustering the intersections, we further obtain the exact location of poles [11]. Appendix A.4 shows an illustration.

3 Results

We randomly retrieve upward street view images using Google Street View API and construct a dataset containing 10,000 samples. Each image is associated with two labels indicating whether it contains lines and whether it contains poles, respectively. There are 3,204 images containing line(s) and 1,786 images containing pole(s) (Appendix A.0). CNNs used in both modules are initialized with weights pretrained on ImageNet. During training, each input image is rotated with an angle randomly selected among $0°$, $90°$, $180°$ and $270°$ and also randomly flipped for data augmentation.

Table 1 shows the classification performance on the test set. The F1 scores (harmonic mean of precision and recall) for both line and pole identification are higher than 92% with precisions over 97% and recalls at around 90%, which indicates superior image-level performance. We also evaluate the region-level performance of our model on San Carlos, CA, USA. Figure 2 shows a small fraction of the distribution grid map reconstructed by our model with the locations and connectivity of lines and poles. We compare the pole localization accuracy of our model with that reported in [11]. The result is shown in Figure 3. The metrics is the percentage of annotated poles that have been detected within a certain range, and its variation with the radius of the range is represented by orange curve for our model, and red curve for the performance reported in [11]. Our model significantly outperforms [11] even though our model is semi-supervised. 78% of the actual poles can be detected by our model within $4\mathrm{m}$, and the average localization error of detected poles is $2.25\mathrm{m}$. Such results demonstrate the benefit of using upward views and the strength of semi-supervised learning.

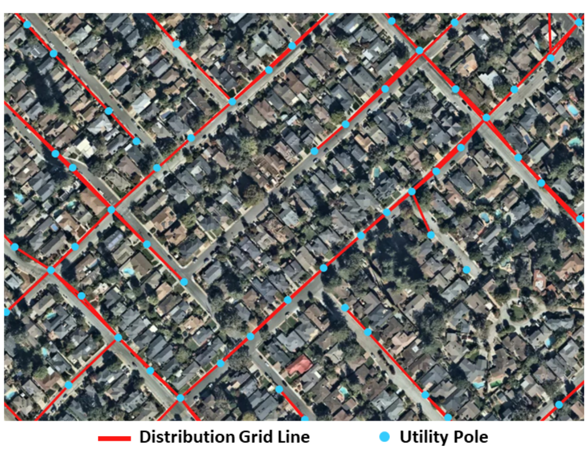

Figure 2: Distribution grid mapping in San Carlos, CA.

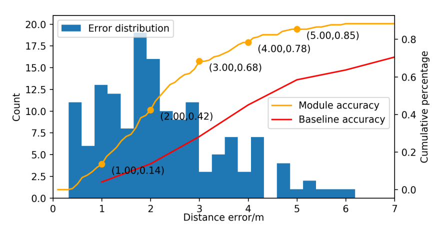

Figure 3: Pole location accuracy

	precision	recall	F1 score
line	0.978	0.929	0.953
pole	0.973	0.882	0.925

Table 1: Classification performance

4 Conclusion and Future Work

In this study, we propose a semi-supervised learning framework to identify and localize utility poles and power lines in street view imagery for fine-grained distribution grid mapping. Future work includes: (1) Identifying the connectivity at crossroads to complete grid topology reconstruction and extend the model to other regions. (2) Combining solar installation database [12] for PV integration analysis. (3) Combining tree inventory and weather data (e.g. wind) for vegetation management (e.g. inform tree trimming to prevent outage) and disaster prevention (e.g. fire risk assessment).

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Appendix

A.0 Dataset construction

To construct the image dataset for line and pole detection, we manually select the images that contain line(s) among the 10,000 samples and get 3,204 such samples. Then we manually select 1,786 images that contain pole(s) among these 3,204 samples, based on the assumption that an image that contains utility pole(s) must contain power line(s). The dataset is finally split into train/validation/test sets following 85%-7.5%-7.5% ratio.

A.1 Hough transform (Line detection module)

Hough transform is a conventional computer vision technique which is used to detect particular shapes in images. It can detect the shape even if it is broken or distorted. The main idea of this approach is using voting procedure to find imperfect instances of objects with a certain mathematical expression.

Here we use Hough transform to detect lines in CAMs. For each line in an image, it can be represented as $\rho = x \cos\theta + y \sin\theta$, where x, y are the pixel positions in the image and ρ, θ are the line parameters. ρ is the perpendicular distance from origin and θ is the angle with respect to horizontal axis. For each activated pixel in CAM, it will vote for a sinusoidal curve in the parameter (ρ, θ) space, which represents all potential lines the pixel may lie in. After all activated pixels have voted, the local maximal points in the parameter space have a high possibility to be a line, thus the line parameters can be detected.

In order to detect multiple lines in an image, we create a mask in the CAM to cover each line once it is detected. All the potential lines can be detected one after another by applying Hough transform to the CAM multiple times.

A.2 Hough transform for angles (Pole detection module)

The Hough transform for angles borrows the ideas from the Hough transform for lines. Because all rays of poles are assumed to pass through the image center, the voting procedure only accumulates among the angles of the lines which pass through the center. And the maximal in the parameter (θ) space represents the possible line.

A.3 CNN architecture

See the Inception-v3 architecture with a branch for generating CAM in Figure 4.

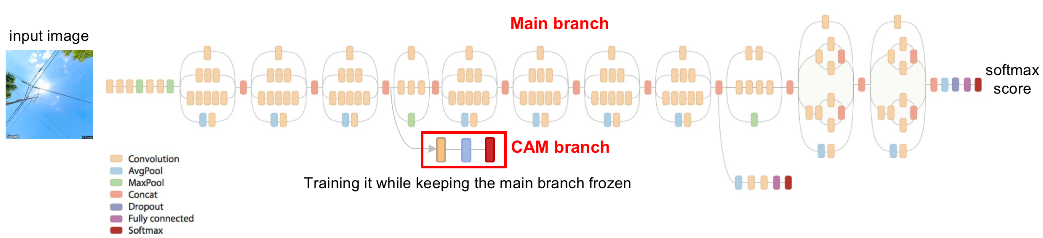

Figure 4: Inception-v3 architecture with a branch for generating CAM.

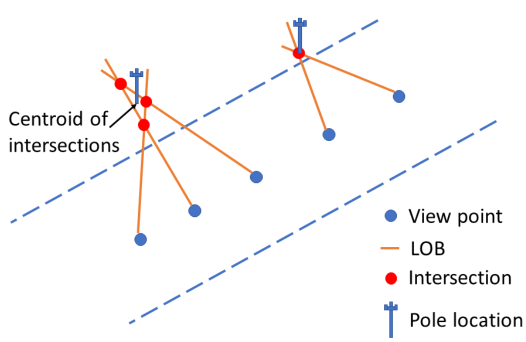

Figure 5: Illustration for cross bearing algorithm

A.4 Cross bearing algorithm

After setting a threshold for the effective radius of a street view image, Any pair of non-parallel line-of-bearings (LOBs) within a certain range can produce an intersection which suggests that there can be a pole at the intersection. Because one pole may be captured by more than 2 upward street views, there can be more than one intersection for a single pole. We use a distance-based clustering method to cluster intersections into groups for different poles. And the centroid of all intersections in a group is used to represent the location of the corresponding pole (See Figure 5).