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Identifying solar arrays from overhead imagery

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ABSTRACT

Residential solar arrays are an increasingly significant source of electricity. When integrated with the electric grid, the weather-dependent production characteristics of solar arrays can pose challenges. For example, if solar array production drops, e.g., due to a sudden change in weather, idle power generation plants need to be turned on, at substantial additional expense. Conversely, if solar production soars, the spot price of electricity may drop, leading to losses. For purposes of grid planning, it is valuable to know the size, orientation and distribution of solar arrays in a given region. Additionally, the availability of a nationwide map of solar-powered rooftops can spur further adoption of solar power. This disclosure provides techniques to determine parameters such as size, orientation, and distribution of solar arrays from analysis of overhead aerial imagery.

KEYWORDS

- Solar arrays
- Overhead imagery
- Electric grid planning
- Maps
- Machine learning

BACKGROUND

An electric grid derives power from a variety of conventional (e.g., thermal, nuclear or hydroelectric), and renewable energy sources (e.g., solar, wind, etc.). Renewable sources such as solar energy form an increasing component of total supplied power. However, such sources are weather dependent. Solar arrays installed at residences return any excess generated power to the grid. Therefore, solar arrays are also a geographically distributed source of energy. These characteristics of solar power complicate grid planning.

For example, in cloudy weather, solar power generation can drop. In order to compensate and avoid brownouts, idle power generation plants need to be turned on. Turning on an idle power generation plant can take hours and involves considerable expense. Therefore, compensatory power from conventional power plants is difficult to make available in a manner that can flexibly respond to weather changes. Conversely, if solar energy production soars, the spot price of electricity can drop, leading to economic losses at power plants.

DESCRIPTION

For proper planning of an electric grid, it is valuable to know the size, distribution and orientation of solar arrays (and other renewable sources) in a given region. Orientation is important since it influences the power-producing ability of a solar panel as a function of time-of-day. For example, west-facing arrays produce more power in the afternoon and less in the morning.

The disclosure describes techniques to determine the size, distribution, and orientation of solar arrays in a given region. Overhead aerial imagery is used to determine size and distribution of solar arrays. A digital surface model (DSM), which is a map of elevation of the earth's surface including surface objects such as buildings and trees, is used to determine array orientation. Machine learning is used to recognize the existence of solar arrays, e.g., by assigning a probability that a given pixel of an aerial image belongs to a solar array. Per techniques of this disclosure, a diverse geographical region, covering different styles of houses, can be analyzed to determine the presence, location, size, and orientation of solar arrays.

Fig. 1: Example aerial image used to detect location and parameters of solar arrays.

Fig. 1 shows an example of an aerial image that is used to detect the presence of solar arrays. Several factors are used to determine if a set of pixels of an aerial image corresponds to a solar array. Further, a type of the solar array, e.g., photovoltaic (PV) or solar water heater (SHW) may potentially be determined. A PV-type solar array generates electricity, while an SHW is used to heat water, e.g., for household use, for a swimming pool, etc.

A solar array is typically between a few meters to about 20 meters on a side. In an aerial image of 10 cm resolution, a solar array can have linear dimensions of between a dozen and hundreds of pixels. As shown in Fig. 1, the shape of a set of candidate pixels, the location near a swimming pool, etc. may be implicitly used to determine the existence and type of solar array. Additional factors such as size, color (deep blue to black), etc. are used to detect the presence of solar arrays. Given a digital surface map, e.g., a map of heights of objects on the earth's surface, the orientation of a solar array can be determined by examining the gradient of a rooftop hosting a detected solar array. For example, if a rooftop is determined by DSM to be south-facing with a tilt of 30 degrees, then the solar array detected on such a rooftop would also have a south-facing orientation with a tilt of 30 degrees.

Per techniques of this disclosure, a machine learner is trained to recognize solar arrays. Such training requires a training data set that includes both positive and negative examples. However, currently available aerial imagery has a relatively sparse presence of rooftop solar arrays, since such arrays are currently installed only in a small fraction, e.g., 1-5%, of houses.

Per techniques of this disclosure, a training set is generated in an iterative approach. An initial small set of aerial images is obtained from geographical regions with high solar power penetration, such that it is known that the region includes a relatively higher percentage of solar arrays. The images are sent to human labelers, who are tasked with providing labels on whether a rooftop in an image includes a solar array or does not include a solar array. The resultant labeled set is used to train a machine learner to recognize rooftops as having solar arrays or not.

The machine learner is used to examine a larger number, e.g., several million, rooftop images. For example, the machine learner generates probability values that a given rooftop has a solar array or not. Rooftops that are identified as having a high probability of a solar array are sent to human labelers, e.g., to verify that the machine learner correctly determined the presence of a solar array. A revised training set is obtained based on the human labelers verification. The operation can be performed iteratively.

In the generation of the training set, a diverse set of aerial images are included, e.g., from regions of high solar penetration, regions of low solar penetration, diverse rooftop designs, diverse geographies etc. The highest available resolution is used. Further, in the aerial images provided to human labelers, rooftops except the target roof that is to be labeled are erased, e.g., blotted out with a red mask, as shown in Fig. 2 below.

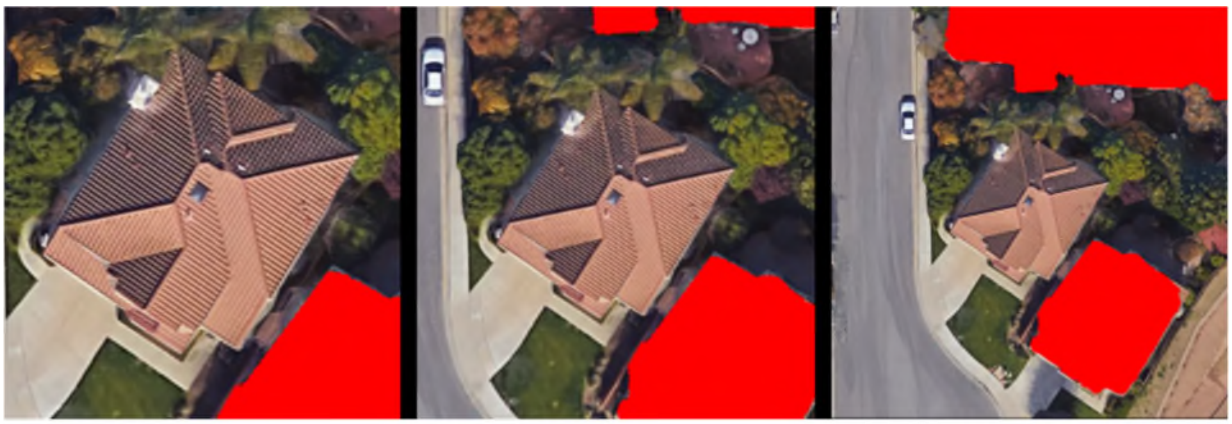

Fig. 2: Example images provided to labelers; resolution decreases from left to right

An example result of running a machine learner on an aerial image is shown in Fig. 3 below. In Fig. 3, the detected solar panels are indicated by orange circles.

Fig. 3: An example of detected solar panels overlaid on a map

Aerial images are derived from a number of sources, e.g., aerial imagery, satellite imagery, etc. Each type of imagery has advantages and disadvantages. For example, some types of images are co-registered with the digital surface mapping. These are more suitable for simultaneously determining the position, size, and orientation of a solar array. Imagery with a relatively higher resolution allows for the most accurate identification of solar arrays. Imagery that's relatively fresh (captured recently) enables an up to date map of solar arrays. In certain areas, imagery of only one type is available. Further, certain types of imagery is updated more frequently, which is advantageous, to ensure that the resultant map is up-to-date. For example, satellite imagery is captured relatively more frequently than other forms of imagery.

CONCLUSION

Techniques of this disclosure provide for the determination of parameters such as the size, location, distribution and orientation of solar arrays from available aerial imagery and digital surface models. Knowledge of such parameters allows power companies to properly predict solar power production, enabling efficient scheduling of power generation by power plants. When the distribution of solar arrays overlaid on a map is available, power companies can focus on neighborhoods to improve solar adoption. Similarly, individual home-owners and prospective buyers can take the step towards solar adoption if they see on a map that their neighbors have done so.