Image Features for Pixel-wise Detection of Solar Photovoltaic Arrays in Aerial Imagery using A Random Forest classifier

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I- Introduction

➢ Provide government agencies, utilities, and third party decision makers access to detailed information about distributed solar photovoltaic (PV) arrays.

➢Obtain information such as locations, power capacity, and energy production of existing arrays in order to make efficient energy-related policies.

➢Propose a new approach for collecting distributed PV information that relies on computer algorithms to automatically detect PV arrays in high resolution aerial imagery.

➢Investigate a new PV detection algorithm based on a Random Forest (RF) classifier.

➢Evaluate its detection performance using several different image features.

II.Aerial Imagery

➢Dataset contains color (RGB) aerial imagery, collected over the U.S. city of Fresno, California in 2013, using ortho-rectified aerial photography, with a spatial resolution of 0.3 meters per pixel.

➢The full dataset used in this work encompasses 112.5 km^2 of surface area, and 2,328 PV array annotations

Figure 1. An Example of Aerial Imagery of Rooftop in Fresno, CA.

III. Random Forest Detector

➢Random Forest is a supervised machine learning algorithm.

➢The input of our RF detector is a set of features of a pixel in an Aerial Imagery and the output of the detector is the likelihood of this pixel being a PV array.

➢The number of decision trees in our experiment is set to be 30 in our experiment.

IV. Feature Engineering

➢ Raw Pixels

➢Color Intensities of the pixels surrounding the pixel we want to classify. The window size is 7 by 7 in our experiment.

➢Local Color Statistics:

➢Local Color Statistics is relatively computationally inexpensive method to characterize the color information in an local neighborhood.

➢It computes mean and variance for each channel in windows surrounding pixels. The windows size in our experience is set to be 3 by 3.

➢Textons:

➢Texton features are a popular class of features that are designed to capture image texture information.

➢Textons require a training step to learn a database of textures and shapes, called a dictionary. The entries in the dictionary are referred to as textons.

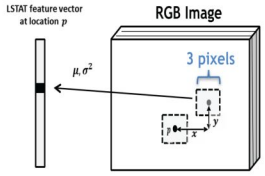

Figure 2. Illustration of Local Color Statistics.

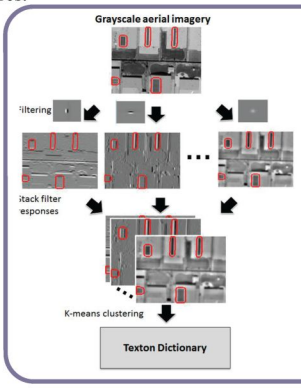

Figure 3. An illustration of the texton feature training procedure. Aerial imagery is filtered with a bank of filters. In this work the Leung-Malik (LM) filter bank is used [30], with 6 orientations, and 2 scales (36 total filters). The filtered images are stacked together, where each pixel is represented by a vector of 36 values, corresponding to its filter responses. The vector of filter responses for each pixel is then used as input to a K-means clustering algorithm, which learns K representative, or common, filter response vectors, which are called textons in this context. In this work K was set to 30. The textons are learned on gray-scale imagery rather than the original color imagery.

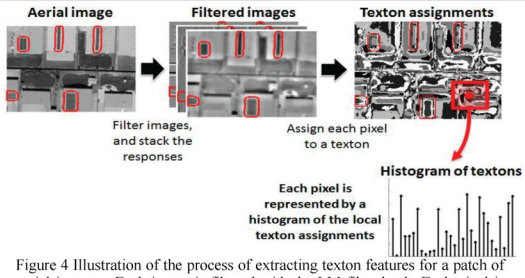

Figure 4 Illustration of the process of extracting texton features for a patch of aerial imagery. Each image is filtered with the LM filter bank. Each pixel is assigned to a texton based on its responses to the LM filters. This results in an image where each pixel is represented by its texton assignment. There are thirty textons, so each pixel receives a value between one and thirty. The feature vector for a given pixel consists of a histogram of the texton assignments in a centered 9x9 window.

V. Experimental Result

➢Use all available PV pixels and randomly sample non-PV pixels for training and testing.

➢Evaluate solar panel detection performance using Precision Recall Curves

➢LCS Feature outperforms other features individually.

➢LCS+Texton achieves the best result with trade-off of computational costs.

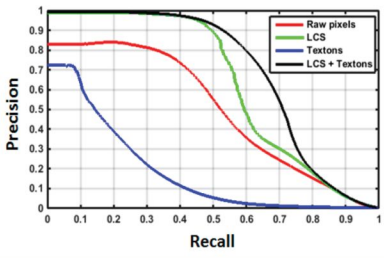

Figure 5. Precision-recall curves for the RF classifier for the different feature sets investigated in this work.