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Article

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Short term prediction of sun coverage using optical flow with GoogLeNet

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Abstract

One of the challenges of PV power generation is solar intermittency from weather conditions. Solar irradiance prediction is therefore required to deal with this issue. Several prediction methods have been proposed based on whole sky image processing techniques. This paper presents a combination technique of image processing with a convolution neural network (CNN) based on GoogLeNet for raising trigger events before the sun cover happens 1 to 2 min in advance. The captured sky images are preprocessed and in the next step, we use Hough transform to find the sun position and use optical flow to track cloud movement. Finally, we use a CNN to generate trigger events in advance before the sun occlusion happens. The results of prediction stage show error percentage as low as 5.26% in a clear sky day.

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Keywords: Ground base sky image; Photovoltaic power forecasting; Solar irradiance; GoogLeNet

1. Introduction

Solar power is among one of the promising renewable energy sources these days with rapidly increasing installed capacity worldwide. Bellini [1] revealed in NEA report that China's installed PV capacity reached 174.63 GW at the end of 2018. However, one of the challenges of PV power generation is solar intermittency from weather conditions. Solar irradiance prediction is therefore required to deal with this issue.

Several methods are reviewed by Tuohy et al. [2] and one of the proposed techniques is based on whole sky image for plant operators to forecast PV power output and help in planning and operating of the PV system. Time scale of the forecast could be classified into long term, medium term, and short term depending on applications. This paper focuses on a short-term prediction to detect rapid change in solar irradiance which directly affects the operation of the smart grid in terms of system integration, power quality, and ramp rate control, Sun et al. [3] presented short term sun occlusion prediction using ground-based all-sky imager and applied the optical flow and

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sun back-propagation methods to track the cloud coverage area. The method predicts occlusion percentage up to 20 min in advance. The accuracy the method is high for a one-minute time scale and declines for much longer time scale. Sayeef and West [4] presented another use of an optical flow method to calculate the direction and velocity of the clouds and use artificial neural networks (ANN) to identify the clouds with potential to block the sun as shown in Fig. 1. The predicting image is compared with the ground truth image pixel by pixel to evaluate the accuracy. This method needs a proper threshold setting to suit different applications and time-step prediction is fixed to 10 s. The other method from [5] applies deep learning as a prediction system to estimate a value of photovoltaic power output up to 10-min forecasting. The trained images were labeled from PV output value. They found that a long short-term memory (LSTM) module outperforms other approaches on a 1-min PV power prediction task. Enough trained images are required especially on a partially cloudy day, nonetheless.

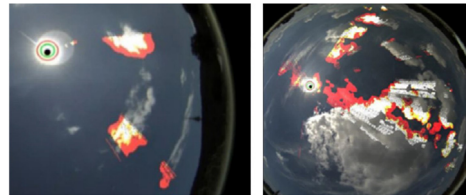


Fig. 1. Examples of dense optical flow’s ability to identify multiple cloud layer movement in different directions.

Most prediction methods utilize the whole sky image with fish-eye angle lens for prediction. However, to promote the prediction system as an integral part of residential or community solar power schemes, a more affordable camera will be required. This paper, therefore, attempts to use an ordinary action camera with a narrower angle lens for prediction. The proposed method reduces the region of interest (ROI) to only a part around the sun radius that is expected to cause sun occlusion within 1 to 2 min time frame. This paper presents a combination technique of image processing and a convolution neural network (CNN) based on GoogLeNet to predict an event of rapid solar irradiance. The proposed method will generate a trigger in case of potential cloud coverage events 1 to 2 min in advance. The rest of the paper is organized as follows. The image preparation and extraction of features procedure are introduced in Section 2 followed by a description of the solar irradiance fluctuation forecasting model in Section 3. After that, the algorithm is tested, and the results are presented in Section 4.

2. Image processing for cloud movement tracking

2.1. Image capture and preprocessing

Sky images are captured at 1280 × 960 pixel resolution every 20 s automatically using a SJCAM-SJ4000 camera, which is installed at the rooftop of the building pointing toward the sky (Fig. 2(a)). The acquired image will be converted so that it is easier to segment clouds, the Sun, and background sky see Fig. 2(b). Eq. (1) shows a resulting layer I as a result of the sum of differences between RGB values of each pixel.

$$I(i, j) = |R(i, j) - G(i, j)| + |G(i, j) - B(i, j)| + |B(i, j) - R(i, j)|, \tag{1}$$

where R represents a pixel in red layer, G represents a pixel in green, B represents a pixel in blue.

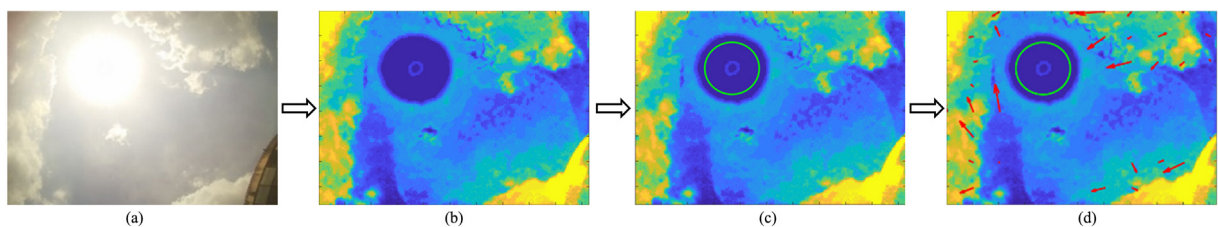


Fig. 2. Sequence of image preparation for better cloud tracking . (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.2. Finding the sun's position

The position of the sun is located using Hough transform technique. This technique had been proposed by Kierkegaard [6]. It is a reliable method to find a circle around the sun radians, as shown in Fig. 2(c).

2.3. Cloud movement tracking

In the next step, we estimate the vector direction and velocity of a moving cloud using the optical flow method with algorithm that was proposed by Farnebäck [7], as shown in Fig. 2(d), where the red arrows indicate vector direction and velocity. The vector information is then broken up into XY parts and represented in a newly created RGB image, in which a vector value in X-axis is a value in Red layer and a vector value in Y-axis is a value in Green layer as shown in Fig. 3. The purpose of doing this is for conveniently applying the vector information to CNN.

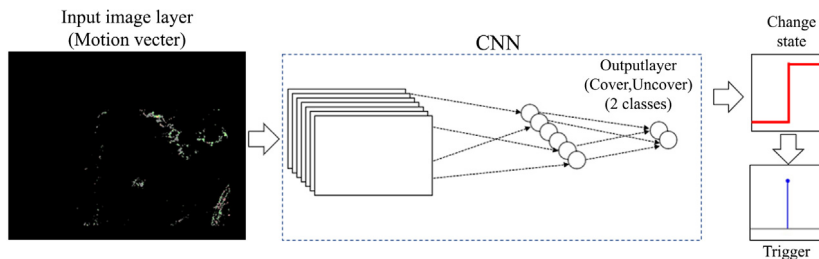


Fig. 3. Convolution neural network for raising trigger events in advance. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The obtained image will have the sun position fixed to the center of the image to normalize every image sent to the prediction system regardless of the time of the day. The image is also resized from 1280×960 down to 256×192 pixel to speed up processing time. The finalized image will then be used as an input for training and testing in the proposed CNN prediction model whose details will be given shortly in the next section.

3. Solar irradiance fluctuation forecasting model

Cloud motion vector image and the position of the sun from Section 2.3 are the input to the CNN to generate a trigger before a cloud moves to cover some part of the sun as shown in Fig. 3. In this work, our network design is based on the network of Szegedy et al. [8] which is GoogLeNet, is a popular CNN tool for image analysis and can be used to classify or predict images with resemble appearance efficiently. The results of the prediction will be compared with another CNN model — Alex net. The network training and the layers setting up will be explained in the following.

3.1. CNN with GoogLeNet setup

We fill the top and bottom of the image with the black pixel to create a square image with a size of 256×256 before being applied to GoogLeNet. Then we adjust the input layer of the GoogLeNet to match the image size and modify the last fully connected layer from 1000 classes to 2 classes since we have only 2 classes of sun occlusion event cover and not cover. Other parameters are set to 0.0001 learning rate, 100 epochs, and 16 mini-batch sizes. These parameters are obtained experimentally to suit our image set.

3.2. Network training

The total number of 10,475 motion vector images from sky images captured from November 2018 to May 2019 for 20 days during 10:00 am to 3:00 pm was used to train the network. Labeling was according to a LDR light sensor used to signal cloud coverage events. In order to generate a 2-min prediction system, we shift forward a “trigger” label of the current image to the image taken 2 min earlier. As an example, in Fig. 4.(b), the cloud has a tendency to block the sun and this is labeled “trigger” because of the real occlusion event 2 min later as shown in Fig. 4.(c).

Table 1. Sun coverage and trigger.

Date	GoogLeNet			Alex net
	● Correct trigger	○ Miss event (All events)	Error (%)	Error (%)
14 Nov 2018	18	1(19)	5.26	42.10
11 Mar 2019	12	2(14)	14.29	21.42
10 May 2019	18	5(23)	21.74	26.09
Total	48	8(56)	14.29	28.57

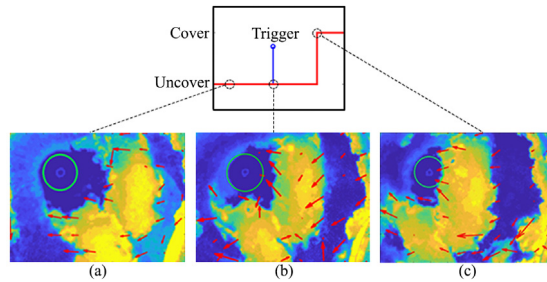


Fig. 4. Example of the case that raising trigger events (a) at 11:51; (b) at 11:53; (c) at 11:55.

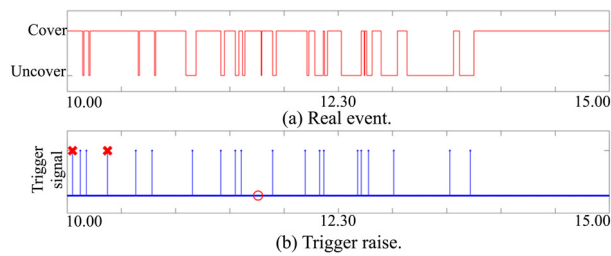


Fig. 5. Result of the predicted trigger on 14 Nov 2018.

4. Forecasting accuracy

To evaluate the accuracy of the proposed prediction system, we used 2195 sky images captured on 14 Nov 2018, 11 Mar 2019, and 10 May 2019 for testing. The trigger events generated in each day were checked with the real sun occlusion events to verify the 2-min warning system. Figs. 5 to 7 compare the predicted trigger with the real sun coverage event where a correct trigger is shown with blue marks and a false trigger is shown in red crosses.

In a winter day of 14 Nov 2018, there were 19 sun coverage events and the system raised triggers 20 times with 18 correct triggers, and 2 false triggers and a single missed event (shown as a red circle in Fig. 5(b)). In a summer day of 11 Mar 2019, there were 14 sun coverage events. The system raised correct triggers 12 times and missed 2 events as shown in Fig. 6(b). On the clear sky, the system accuracy is high. However, on a cloudy day of 10 May 2019 during the rainy season that gave 23 sun coverage events, the system raised trigger totally 18 times correctly. But several missing events were presented 5 times as shown in Fig. 7(b).

The overall accuracy of the method is compared with the prediction system based on Alex net using the same set of trained and test images. The results are given in Table 1. Krizhevsky et al. [9] have present a new CNN, Alex net, which is among the first deep learning model and therefore it is usually used as a fundamental model for applying deep neural networks. From Table 1, the overall results for 3 days of test data show an error (false and missed events) of 14.29% with the best of 5% error on 14 Nov 2018 while Alex net method yields an error of 28.57% in overall. Clearly, the method based on GoogLeNet has better prediction rate than that of Alex net.

The characteristic of clouds on 14 November that result in the best prediction (only one miss event) is thick and clear as shown in Fig. 4. The moment that a trigger generated can be determined easily by the network with accurate sun coverage event 2 min later. On the contrary, the cloud characteristic on 10 May with high error percentage shows

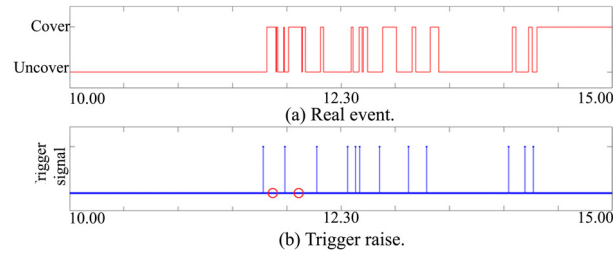


Fig. 6. Result of the predicted trigger on 11 Mar 2019.

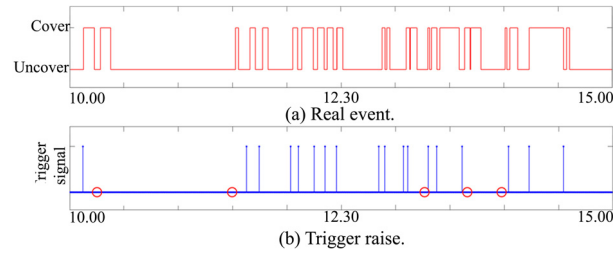


Fig. 7. Result of the predicted trigger on 10 May 2019.

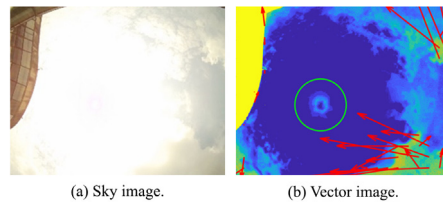


Fig. 8. Cloud image on 10 May at 11:29.

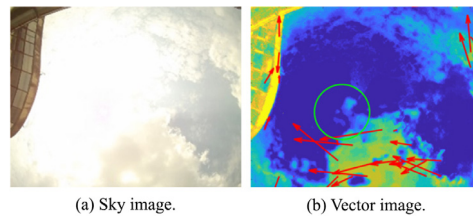


Fig. 9. Cloud image on 10 May at 11:31.

a thin pattern cloud casting over the sky. This type of cloud generates confusion in determining cloud movement vectors as shown in Fig. 8. The glaring sun causes a problem in detecting the area of the cloud and the vector is unreliable to raise trigger when the cloud touching the sun 2 min late as shown in Fig. 9. This cloud pattern needs to be investigated further in future work.

5. Conclusion

In this work, we have proposed an approach for short-term forecasting of an event of sun coverage with CNN based on GoogLeNet method. This method can raise trigger before the cloud moving to partially cover the sun 1 to 2 min of events really occur. The accuracy depends on the cloud characteristics. In winter when the sky is clear and thick cloud presents, this condition yields much higher accuracy than cloudy sky in a rainy season with confusing cloud movement. The error of the prediction is as good as 5% in a clear sky day. However, an error on

a thin pattern cloud casting over the sky tends to be higher and requires further investigation in the future work. Also, more trained images can help increasing the accuracy. The accuracy was compared with the method based on Alexnet and found to be better in every test case. Better capturing and preprocessing techniques could result in an improved prediction rate.

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