Intelligent Fault Pattern Recognition of Aerial Photovoltaic Module Images Based on Deep Learning Technique

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ABSTRACT

The rise of photovoltaic industry has raised the difficulty of the operation and maintenance. Nowadays, the growing interest in the application of unmanned aerial vehicles (UAV) in civil monitoring and diagnostic applications has been observed. Such UAV-based inspection system can significantly improve the efficiency of system monitoring and fault detections. This paper presents an intelligent UAV-based inspection system for asset assessment and defect classification for large-scale PV systems. The aerial imagery data of PV modules increase the complexity of the detection by traditional pattern recognition, a novel method based on the deep learning and supervision is proposed, which could solve the low quality and distortion flexibly and reliably. A convolutional neural network (CNN) is adopted to address the defects classification. Extracting features by the pre-trained architecture Vgg16, the suggested solution added a full-connected layer and a SVM decision layer to classify the defects. Such pre-trained learning-based algorithm can meet the demand of the small datasets, and carry out a variety of deep features and condition classification in PV system, which can supervise with significantly promoted efficiency in comparison with the conventional methods. The proposed solution is evaluated through numerical experiments and the result confirms its improved performance.

Keywords: UAV, PV inspection, CNN, and Defects classification.

1. INTRODUCTION

Currently the solar energy has been playingplays an increasingly important role in the transition to a clean and low-carbon energy provision globally. The statistics from International Energy Agency (IEA) indicates that, the worldwide deployment capacity of about 55 GW is accomplished in 2015, and installed capacity is projected to more than double or even triple beyond 500 GW between 2015 and 2020 [1]. The deployed large-scale Photovoltaic (PV) PV farms plants are often located in remote areas, e.g. in plains, hills or large workshop roof with no obvious sun shading areas, as illustrated in Fig. 1.

Such large geographical scale and dispersed location bring obvious challenge for system inspection ([2], [3]). Conventional manual inspection through visual assessment of individual PV modules can be cost prohibitive with high error rate, and even not feasible [4].

In recent years, Unmanned Aerial Vehicles (UAVs) has been adopted in many civil areas, e.g. electric power line inspection, with significantly improved efficiency and flexibility. With the onboard cameras and microprocessor, the UAV based patrolling system can provide a non-destructive, reliable inspection of large-scale PV farms. Though the processing and analysis of the obtained large number of aerial images, such UAV based inspection system can cost-effectively carry out real-time condition monitoring and fault diagnosis and prognostic analysis.

Fig.1 The illustration of a large-scale PV farm

With long time running in the environment with UV, high temperature, and moisture will accelerate the oxidation and failure [5]. The severe encapsulant delamination can increase reflection so that the irradiance will be decreased, and water will sink in the modules, leading to the acceleration of cell oxidation [6]. The accumulation of dust can directly reduce the light transmittance and affect the efficiency of photovoltaic power generation system [7], sometimes can reach about 50%, and even worse to 80% . Although snail trails don't have direct impact on the power generation efficiency, it is generally associated with invisible cell cracks, which will decrease the output [8].

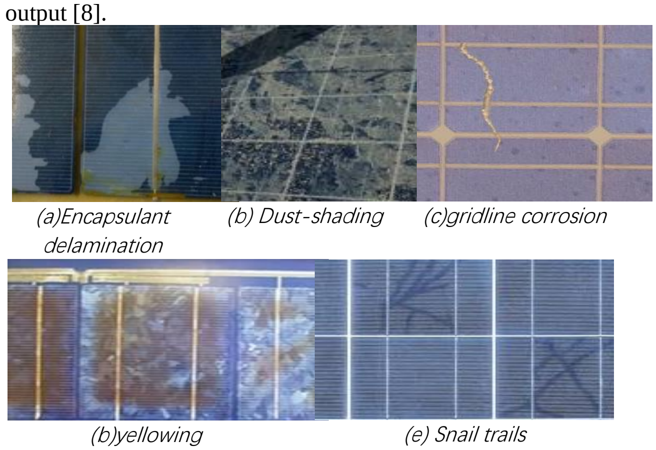

***Fig.2** Different forms of common visible defects and faults in PV modules*

Our previous work [9] has addressed the diagnosis of visible PV module defects and confirmed the effectiveness of the image processing based fault analysis. However, the performance of such approach can be significantly degraded if the obtained images are with low resolution due to many reasons, e.g. wind effect. In addition, the conventional pattern recognition algorithms are often not able to accomplish the fault feature exactions from the obtained aerial images with acceptable complexity. The defects are various, the foreknowledge of the features is defined and fixed, which means it is limited by the people's cognitive abilities and has poor robustness. A more efficient and robust classification methods isare urgently needed to classify different kinds of faults defects.

Motivated by the improved performance of deep convolutional neural network, artificial intelligence learning algorithm is introduced into the intelligent patrolling system to improve the robustness and reliability. The Deep Neural Networks (DNN), in particular the Convolutional Neural Networks (CNN) has shown superior performance on almost all kinds of image classification tasks [10]. It is known that the CNN is a kind of artificial neural network based on multilayer supervised learning. It can extract certain deep features automatically, and it has high fault tolerance, self-learning and adaptability. Another significant advantage is that the effect classification based on CNN will be more accurate with the accumulation of datasheet.

The deep CNN architectures trained on ImageNet can extract much more representative features than other state-of-the-art systems on various tasks [11], which comprises 13 convolution layers, five of each followed with pooling layers, and three fully-connected layers. Thus, instead of training the CNN architecture on scarce PV module images, we directly apply a pre-trained model to extract off-the-shelf features for PV module classification. Based on the well-known pre-trained Vgg16 architecture, we add we add a full-connected layer and a SVM decision layer, which has outperformed than soft-max or KNN models [12] on small datasets, and the non-linear and high dimensional features.

To this end, inspired by the discriminative characteristics of these deep features, this paper presented a novel and intelligent defect diagnose method from aerial images based on deep convolutional neural networks. To the author's best knowledge, little work has been carried out to adopt deep CNN in fault diagnosis of PV module failures. The main contributions made are as follows: (1) an automatic UAV-based inspection system is implemented for PV module defect detection based on aerial images for large-scale PV systems; and (2) the a deep CNN based PV defects diagnosis method is presented; and a modified deep convolutional neural feature extraction method is applied for PV defects status feature description;

The rest of the paper is organized as follows: Section I briefly overviews the UAV-based inspection system for large-scale PV farms; followed by the discussion of deep CNN architecture and typical PV module defects given in Section III3; Section IV4 presents the proposed solution in details with a set of numerical results; and finally the conclusive remarks are given in Section V.

2. UAV-BASED INSPECTION SYSTEM

The model of proposed UAV based inspection system for monitoring and fault detection of PV farms is represented in Fig.3, where an UAV performs a mission flying over a photovoltaic field to collect optical images of solar panels in a PV plant. The basic configuration is as follows:

- DJI M100 open source aircraft
- DJI Zenmuse X3 optical camera and gimbal
- Manifold as on-board computer

Given the geographical information of the PV systems and the cruising scope, the airborne processor can plan a patrol route and implement image acquisition. In the meantime, the imagery data of PV modules captured by the camera are transmitted to the Ground Control Station (GCS) via wireless communication network.

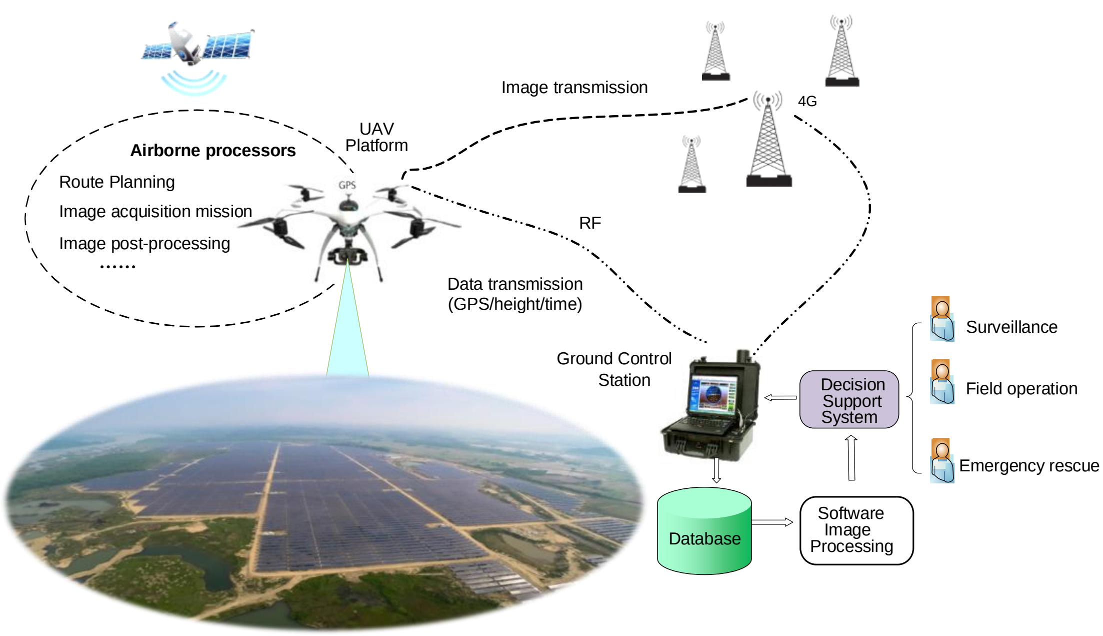

***Fig. 3** UAV based inspection system for monitoring and fault detection of large-scale PV farms [9].*

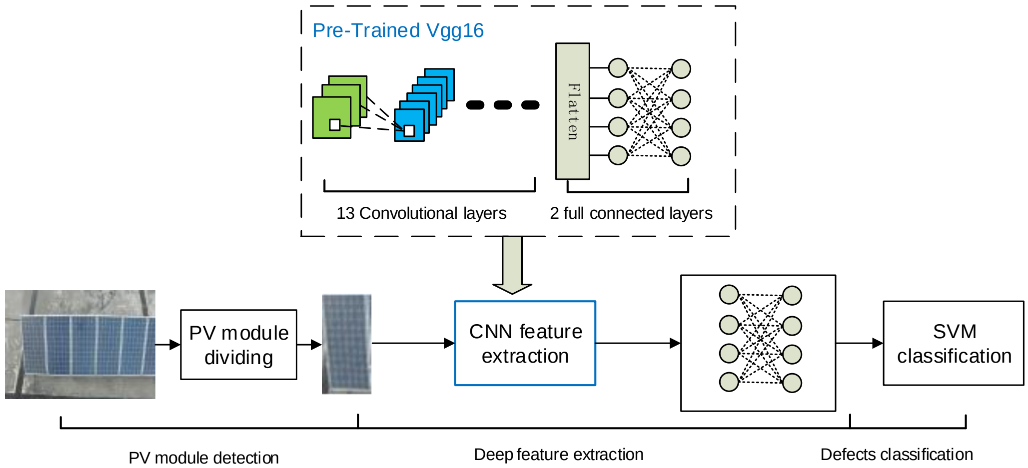

Fig.4 *the architecture of CNN*

Later on, the imagery data is provided to the GCS in charge of defect identification and PV plant management for further corrective control or maintenance tasks. Processing the data stored in the database and classifying the defects, the processed information will be sent to the decision support system. Corresponding measures will be taken, like washing up or changing PV modules.

Based on the previous experimental tests and datasets, there is comprehensive information about PV modules condition in the database. Even though, the training of the learning and extraction algorithm costs few hours, the prediction and classification will be finished in seconds in the trained network.

3. CNN ARCHITECTURE FRAME

In section 2, some common visible PV faults are mentioned. These defects generate different shapes because of the complex environment and factors. It is quite difficult to recognize these types. However, the PV modules from aerial images vary extremely from aspect ratio and orientation. In addition, the models will consist of some noises and the perspective distortion caused by the flight mission itself, which are different form general image datasets, such as Razavian [13]. This is a solution of segmentation of the PV module subsets.

The overall flowchart of the proposed PV module inspection method is shown in Fig. 4 pre-trained network Vgg16 is applied to extract CNN features and then a SVM is trained to classify the difference.

As depicted in Fig. 4, the net contains 17 layers with weights; the first 13 are convolutional and the remaining four are fully connected. The output of the last fully connected layer is fed to a n-way SVM which produces a distribution over the n class labels.

The pre-trained Vgg16 architecture consists of 13 convolution layers and three full connected layers in sequence, where all output of those layers are applied with the ReLU non linearity. And the kernels of the second, fourth, seventh, tenth and 13rd convolutional layers are followed by a max-pooling layer.

The first convolutional layer filters the 224 × 224 × 3 input image with 64 kernels of size 7 × 7 × 3 with a stride of 2 pixels (this is the distance between the receptive field centers of neighboring neurons in a kernel map). Afterwards, access to the pre-trained Vgg16 to extract the deep features.

We extract the features from the hidden fully-connected layer, and each layer has 4096 neurons, which means we extracted a 4096-dimensional feature. After the feature extractions, we use the SVM classifier to divide the deferent defects.

We implemented our CNN feature extraction strategy in python based on tensorflow, and we randomly cropped 16 patches from the original image and our CNN model with these patch images. Max-pooling and Rectified Linear Unit (ReLU) as non-linearity activation were also applied among these layers.

We trained our models using stochastic gradient descent with a batch size of 16 examples, momentum of 0.9, and weight decay of 0.001. We found that this small amount of weight decay was important for the model to learn. It reduces the model's training error. The update rule for weight w was

$$v_{i+1} = 0.9 \cdot v_i - 0.001 \cdot r \cdot w_i - r \cdot \left(\frac{\partial L}{\partial w} |_{w_i} \right)_{D_i} \quad (1)$$

$$w_{i+1} = w_i + v_{i+1} \quad (2)$$

where i is the iteration index, v is the momentum variable, r is the learning rate, and $\left(\frac{\partial L}{\partial w} |_{w_i} \right)_{D_i}$ is the average over the i^{th} batch D_i of the derivative of the objective with respect to w, evaluated at w_i.

Here, an equal learning rate for all layers is adopted which can be tuned through the training process. To accelerate the training, the non-saturating neurons and computational platform with GPUs are used to carry out the convolution operation.

4. EXPERIMENTAL ANALYSIS AND RESULTS

In this section, we begin by introducing our PV module datasets captured by the UAV system. Actually, this algorithm could classify the difference of the good condition of PV modules and the defects. However, in order to meet the demand of the market, we will first classify the good with the defects. And then, we evaluate our CNN feature extraction strategy with different defects. All the experiments were conducted on a computer with four GPU NVIDIA TITAN. The OS was 64-bit Ubuntu 14.04 and our method was deployed by python.

Datasets

Currently there are no publicly available PV modules datasets which increase the difficulty of the algorithm. Most of these

datasets are collected by the power station and downloaded from Google gallery. In this paper, the images are cropped manually from several pictures captured during UAV patrolling from different places and time in China. All the images are of large amount of noises, distortion and tilted.
Due to the complex imagery datasets, variant illuminations and dynamic view changing, objects (especially defects) from the aerial images are less distinctive. Under this circumstances preprocessing like denoising and image enhancement are performed on aerial images. The defects dataset with different status is constructed, and this dataset consists of 2000 good conditions of PV modules, 1000 bad conditions of PV modules containing of 100 encapsulant delamination, 100 encapsulant delamination, 100 glass breakage, and 500 dust-shading and 200 snail trails. The whole dataset consists of 6 kinds of images. Some sample images in this dataset are shown in Fig. 2.
With the purpose of generating features with more rotation invariance, we modified the network input by random selecting multiple patches of the original images and augmented the number by mirroring operation.

Details of learning

The dataset is separated into training and testing set, and 80% of each class is randomly selected for training and the remaining 20% is for testing. In this experiment, the training and testing features are extracted from the fully connected layers, and both of them are of 4096-dimension. The weights are initialized in each layer from a zero-mean Gaussian distribution with standard deviation 0.01. We initialized the neuron biases in the second, fourth, and fifth convolutional layers, as well as in the fully connected hidden layers, with the constant 1. This initialization accelerates the early stages of learning by providing the ReLUs with positive inputs. We initialized the neuron biases in the remaining layers with the constant 0.
The heuristic which we followed was to divide the learning rate by 10 when the validation error rate stopped improving with the current learning rate. The learning rate was initialized at 0.01 and reduced three times prior to termination. We trained the network for roughly 2000 cycles which took 2 days on four GPU NVIDIA TITAN.

Numerical Result

To validate the proposed solution, two cases are studied: failure/failure-free conditions of PV modules (Table I), and defect type classification (Table II). The defect diagnosis accuracy is evaluated through a comparative study. .

Case 1: Failure/ failure-free conditions of PV modules

In order to meet the demand of the market, we classify two statuses: good condition or bad condition. This is just a binary classification; the output of the last fully connected layer is fed to a 2-way SVM which produces a distribution over two class labels: good or bad conditions. The summarized classification results is shown in Table I. The accuracy of 90.23% is obtained by training SVM with the fc-6 features from the ImageNet pre-trained CNN model Vgg16. The models trained completely on the small PV modules datasets are inferior to the Pre-trained Vgg16 model, which is 67.94% compared with 78.61%.
The features extracted by pre-trained Vgg16 are the features of 1000 objects on ImageNet which does not fit the defects of PV modules. Limited by the small datasets, the non-pre-trained Vgg16 has poor effect. Based on this, our architecture based on the pre-trained CNN has the better effects.

TABLE I. COMPARISON OF RESULTS ON PV CONDITIONS.

Model	Pre-trained Vgg16	Non pre-trained CNN	Our method
accuracy	78.61%	67.94%	90.23%

Case 2: Different defects of PV modules

The task starts from locating the defects and then the insulators are cropped from the origin images. In order to show the effects of our method, different defects are then classified. This part we will do a five-defect classification mentioned in Section 3. The output of the last fully connected layer is fed to a 5-way SVM which produces a distribution over five class labels.
The summarized classification results are shown in Table II, the accuracy of the defects classification is around 80%. Comparing with the pre-trained Vgg16 around 70% or the non pre-trained CNN around 60%, our method is much better efficient. It can be observed that the dust-shading is better than other defects. This is due to the fact that a large scale dataset can better tune the parameters within a deep model and a pre-trained model is suitable for tasks conducted on small datasets. This also proves how powerful the CNN features off-the-shelf are for visual classification tasks.

TABLE II. COMPARISON OF RESULTS ON DIFFERENT PV DEFECTS.

Model	Pre-trained Vgg16	Non pre-trained CNN	Our method
Encapsulant delamination	68.55%	57.50%	78.91%
Encapsulant discoloration	69.13%	56.87%	77.32%
Glass breakage	67.58%	57.00%	76.88%
Dust-shading	76.34%	64.28%	84.40%
Snail trails	67.87%	56.50%	77.82%

5. FORMULAE

This paper presented an automatic UAV-based inspection system for asset assessment and defect detection for large-scale PV systems. The field trail experiment demonstrates that the developed UAV-based system can carry out inspection and condition monitoring tasks in large-scale PV systems in both autonomous and supervised fashion with significantly improved efficiency. The numerical result demonstrates that the effectiveness of proposed solution with a small datasets.
In the future, the performance of the proposed solution can be further enhanced along with the development of aerial image database; In addition, the functionalities of the implemented UAV-based inspection systems needs to be further validated through field trails in large-scale PV systems located in more complex topographies.

6. REFERENCES

[1] International Energy Agency (2014). 'Technology Roadmap: Solar Photovoltaic Energy' (Online) http://www.iea.org
[2] S. Tatapudi, et al., Defect and safety inspection of 6 PV technologies from 56,000 modules representing 257,000 modules in 4 climatic regions of the United States, in Photovoltaic Specialists Conference. 2016.

[3] P. Quater, et al., Light Unmanned Aerial Vehicles (UAVs) for Cooperative Inspection of PV Plants. IEEE Journal of Photovoltaics, 2014. 4(4): p. 1107-1113.
[4] J. Tsanakas, L. Ha and C. Buerhop, Faults and infrared thermographic diagnosis in operating c-Si photovoltaic modules: A review of research and future challenges. Renewable and Sustainable Energy Reviews, 2016. 62: p. 695-709.
[5] S. Mohammed, B. Boumediene and B. Miloud, Assessment of PV modules degradation based on performances and visual inspection in Algerian Sahara. International Journal of Renewable Energy Research, 2016.
[6] M. Köntges, Review of Failures of Photovoltaic Modules', IEA-Photovoltaic Power Systems Programme. 2014: p. 1-140.
[7] A. Tabanjat, M. Becherif, D. Hissel,:'Reconfiguration solution for shaded PV panels using switching control'. Renewable Energy,2015, vol.82,pp.4-13
[8] A. Dolara, G. Lazaroiu, S. Leva, G. Manzolini,:'Snail Trails and Cell Micro-Cracks impact on PV module maximum power and energy production'. IEEE Journal of Photovoltaics, 2016, vol.6, pp. 1269-1277
[9] X. Li, Q. Yang, Z. Chen, et al.:'Visible defects detection based on UAV-based inspection in large-scale photovoltaic systems ' , IET Renewable Power Gemeration,2017.
[10] A. Krizhevsky,., I. Sutskever and G. Hinton, ImageNet classification with deep convolutional neural networks.
[11] K. Simonyan, A. Zisserman,'Very deep convolutional networks for large-scale image recognition', Computer Vision and Pattern Recognition,2014
[12] A. Mekhaldi, and M. Teguar, "Elaboration of novel image processing algorithm for arcing discharges recognition on HV polluted insulator model," IEEE Transactions on Dielectrics and Electrical Insulation,vol. 22, no. 2, pp. 990-999, 2015.
[13] A. Razavian, H. Azizpour, H. Sullivan, and S. Carlsson, "CNN features off-the-shelf: an astounding baseline for recognition," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), pp. 512-519, 2014.