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"Optimal productivity in solar power plants based on machine learning and engineering management"

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Optimal productivity in solar power plants based on machine learning and engineering management

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Abstract.

The complexity of solar power plants is constantly increasing. This sophistication includes the increasing number of solar panels installed and the technologies that are employed in the energy conversion systems. The new solar plants require advanced methods to ensure the availability of all the panels. This paper proposes a recurrent convolutional neural network algorithm for detecting failures, reducing the costs and the time of the inspections. The method is aimed to analyze the data provided by an unmanned aerial vehicle fitted with a thermographic camera. This system provides thermographic data and telemetry. A region-based recurrent convolutional neural network is trained by a previously created dataset. Once the neural network is trained, it is used as a hot spot detector. This detector will have employed the telemetry in order to identify the real panel that can be affected.

Keywords: Renewable energy, reliability, solar photovoltaic, unmanned artificial vehicles, thermography, recurrent convolutional neural network.

1. Introduction

Renewable energy is increasing their power production against to the conventional energies due the international policies in most of the countries [1-4]. This growth must to supply the increasing demand of the global energy demand [4-6].

The solar energy is one of the most important renewable energy with more than 291.064 MW global installed capacity. The growth of this renewable energy is an evidence due to this capacity was only 8.781 MW in 2007 [7]. The size of the solar power plants is also increasing, covering areas of thousands of square meters.

The large extension of solar plants allows the capacity of solar plants to be increased, e.g. 1.000 MW of the Solar Quaid-e-Azzam in Punjab, Pakistan [8]. This trend is due to high demand of renewable energies. Therefore, the modern solar plants require expensive operation and maintenance (O&M) tasks, e.g. panel cleaning, lubrication, repairs and general inspections of the complete installation. The O&M costs are approximately 11,27 €/KW in a ground installation [9]. It is necessary to find efficient methodologies and tools to reduce the O&M costs and ensure the availability of the solar panels. These new tools should be applicable to preventive and predictive maintenance [10-13].

The companies are managing the maintenance based on the Supervisory Control and Data Acquisition (SCADA). There are a large number of approaches employed in SCADA systems [14,15]. The operators take decisions according to analytics methods [10,16,17], where in fault detection and diagnosis have been studying novel techniques in the last few years [18-20]. Condition-based maintenance systems are widely employed for the wind energy systems to improve the O&M process [13,21,22]. These systems allow useful information about the condition of the panels. This information can be used to check the status of equipment, identify potential problems before failures occur, minimize downtimes, schedule relevant repairs and maximize the efficiency of the conversion processes [23-25]. Since the number and the complexity of the components are growing, it is crucial to employ new technologies in the development of maintenance management strategies [10,26].

The main objective of this paper is to present an advanced processing method for detecting hot spots on solar panels. The method is applied to thermal images provided by unmanned aerial vehicles (UAVs) based system [27]. This system allows the operators to obtain a large amount of data in few minutes. The infrared and visual cameras can be employed to detect hot spots that can be associated to certain failures, e.g. damaged cells, short circuits and fire hazards. The UAV based system also provides telemetry that can be used to ubicate the hot spot detected in the specific panel.

The proposed method is developed to analyse automatically these data. A recurrent convolutional neural network (R-CNN) based detector is employed in order to identify the panels and the possible defects or damages. A final report is obtained where the thermographic results are considered together with the GPS position. This information facilitates the maintenance management due to it is possible to map the location of all the hot spots of the solar power plant.

2. Problem description

The method proposed in this paper is employed to process the data provided by a condition monitoring system embarked in a UAV. This system combines thermography and UAVs. The thermography is carried out by infrared (IR) camera that is able to measure infrared energy. The UAV operation could be carried out manually by operator or automatically introducing the correct route by GPS. The image acquisition needs a reliable equipment, capable to obtain high quality images even several meters above ground. For this purpose, UAVs must be complemented with a stabilization system, i.e. a gimbal [27].

Two different types of dataset are acquired by this system. On the one hand, thermographic camera captures IR images. These images are composed of a matrix with the temperature of each pixel. This matrix is converted into a colormap image using a specific software. On the other hand, telemetric data (GPS coordinates, altitude, orientation) is provided continuously by the UAV. Figure 1 shows a basic scheme of the complete system.

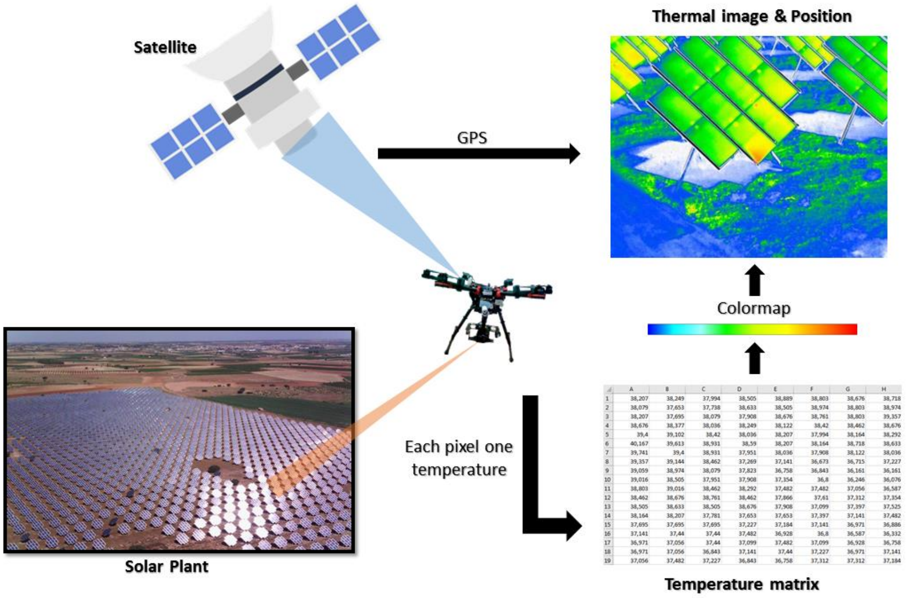

Figure 1. Acquisition data and image composition

The temperature matrix acquired generates a large amount of data, e.g. ten minutes of thermal video can collect about 2 Gigabytes. Different files are provided by the system such as image, video, radiometric image or temperature matrix.

Each solar panel is different, and the solar tracks can have different positions. Figure 2 shows different panel compositions according to the type of solar track. Generally, the solar power plant presents a distribution similar to the presented in Figure 2 (below) if the panels are fixed. Figure 2(top) shows a power plant based in solar tracking installation, with one or two axes.

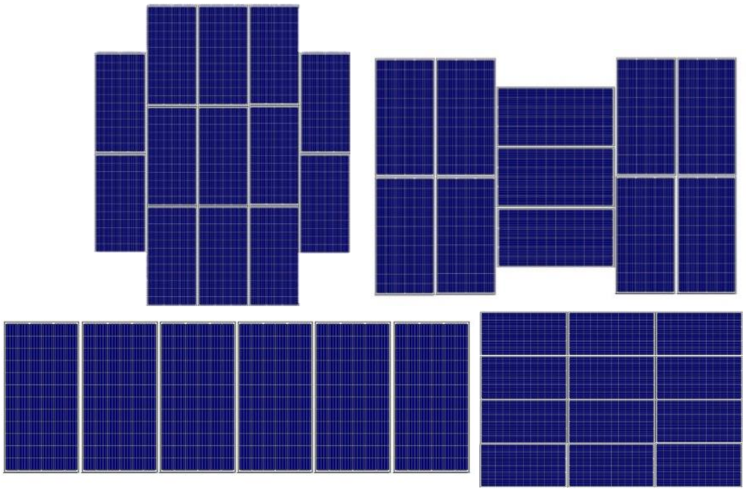

Figure 2. Different panel composition: solar tracking installation, with one or two axes (Top); fixed (Down).

The orientation of the UAV and the IR camera during the flight is decisive for the inspection. The best images are taken in front of the panels. The date and the hour of flight are very important variables due to reflections. A previous study is needed to determine the position of solar trackers at the flight time to avoid reflections. Reflections could be confused with hot spot in thermal images and, i.e. with failures of the panels.

A frame usually contains several panels, foreground and background. A method is needed to avoid duplications when a panel has been detected and analyzed, due to a panel, or set panels, can appear several times in different frames.

The patterns of the different failures are employed to determine the type of failure to consider. Figure 3 shows thermographic patterns that commonly appears in IR images [28].

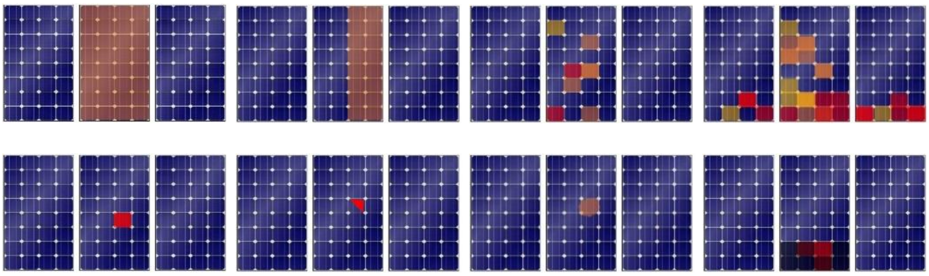

Figure 3 Different thermographic pattern

3. Approach

The data acquisition system, composed by a UAV and IR camera, provides two types of dataset: telemetry and thermal images. This paper is aimed to consider these data as inputs of a R-CNN [15,29,30], in order to extract information of the condition of the solar panels. This technique has been developed to improve the performance of conventional convolutional neural networks (CNN). The R-CNN method obtain excellent accuracy to classify object proposals. It presents some disadvantages, e.g. the training process requires a large computational cost, the object detection is slow, etc. Figure 4 shows a basic overview of the detection scheme. An input image is taken, and the regions to study are extracted. Then, it is computed by a CNN and, finally, each region is classified.

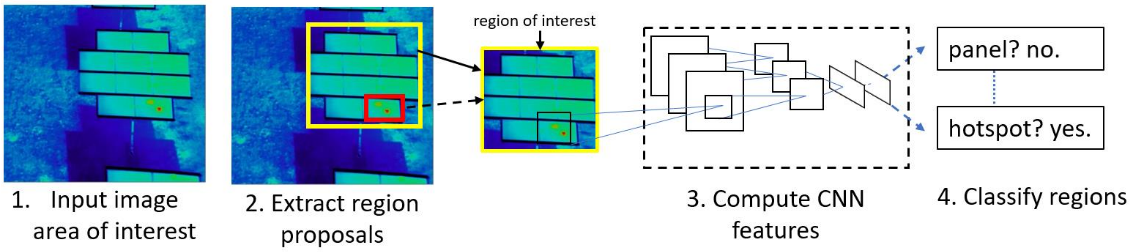

Figure 4. Object detection system overview

The algorithm is divided in three stages. Firstly, a R-CNN is trained with massive data. Then, the R-CNN is ready to process new data provided by the data acquisition system. Finally, some results are provided considering both telemetry and thermal images. Figure 5 shows a basic scheme of the method.

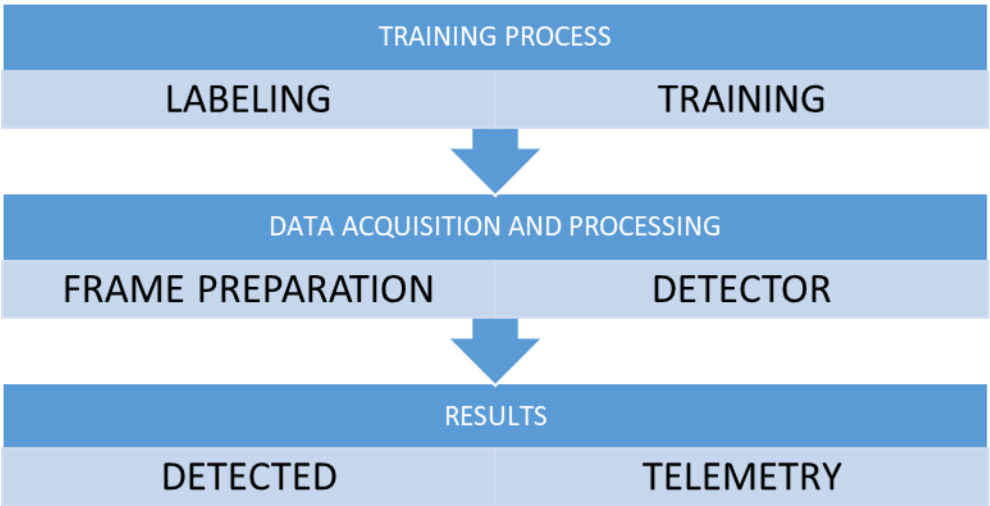

Figure 5. Basic scheme of the proposed method

a) Training process

The process starts with the creation of a database using hundreds of images of solar power plants with different types of panels, shapes and orientations. The training process can be carried out when the database is created, and it requires a previous selection of the region of interests (ROIs). These regions are the area of each image in which are located the information of panels and hot spots. Each ROI is defined by the location in the frame and a label about the content.

Figure 6 shows an example of two different ROIs. The yellow boundary box corresponds to the label “panel”, and the orange boundary box corresponds to the “hotSpot” label. A manual labeling process is required. The quality of the final outcome will depend on them although there are a lot of training images.

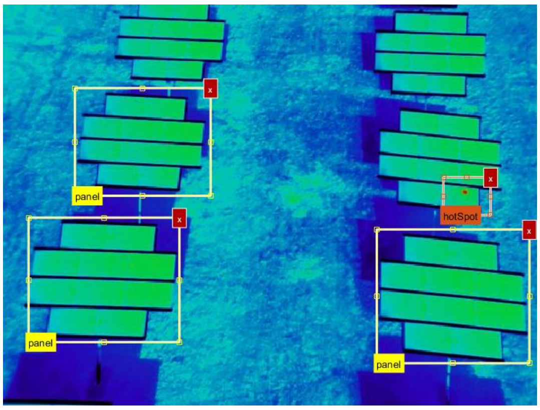

Figure 6. ROIs definition during the R-CNN training process

The images are ready to be inputted in the trainer when the labeling process has finished. Several parameters can be adjusted in this process, depending on the features of the detector. For example, the optimal number of epochs must be defined. If the number of epochs is not correct, the efficiency can decrease.

The neural network is organized in different types of layers:

- *ImageInputLayer:* It is the first layer in the network. This layer is in charge of inputting an image and applying data normalization.

- *Convolution2DLayer:* This layer applies sliding filters to the input. It executes a convolution moving the filters vertically and horizontally. The layer calculates the dot product of the weights and the input.

- *MaxPooling2DLayer:* This layer develops a down-sampling. The input is divided into rectangular pooling regions. The maximum of each region is computed too.

- Rectified Linear Unit *(ReLULayer):* This layer establishes a threshold in each input element where any value less than zero is set to zero. It is defined in the next equation:

$$f(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

- *AveragePooling2DLayer:* This layer divides the input into rectangular pooling areas and obtains an average of values in each region

- *FullyConnectedLayer:* In this layer, the input is multiplied by a weight matrix and a bias vector is generated.

- *SoftmaxLayer:* This layer applies a normalized exponential function.

- *ClassificationOutputLayer:* This layer classifies the output of the neural network.

The training process begins when the structure of neural network is built. This process is a complex task that could take several hours, even days, depending on the amount of images, boundary boxes and labels, as well as the GPU, or CPU, characteristics. Once the R-CNN is trained, it is ready to receive real images from the data acquisition system.

b) *Data acquisition and processing*

The data employed in this paper is provided by a condition monitoring system embarked in UAV. This system can provide telemetric data and thermal images of the solar panels. Therefore, the data collected is composed of telemetry and thermal recordings (videoframes or photography).

All the telemetric data must be known when the images are collected. These telemetric data include altitude, orientation, GPS position, camera angle and vision angle. The telemetry will be incorporated in a final report in case of hotspot detection to avoid additional computational costs.

Regarding to the thermal recordings, the first element of the image acquisition process is the thermographic camera. The camera can take photos or record videos that can be analyzed frame by frame. Each frame will be associated with a specific telemetry.

The method requires a preprocessing stage in order to prepare the frames to be inputted in the R-CNN. The first stage is to adjust the orientation of the panels. Due to the ROIs are rectangular, the R-CNN works better if the edges of the solar panels are perpendicular to the edges of the images. For this purpose, a specific algorithm has been developed. Figure 7 shows the different steps of the image rotation from left to right. The original image is showed on the left (Figure 7). The main edges of the solar panels are shown in the middle of Figure 7. Finally, the rotated image is shown on the right of Figure 7.

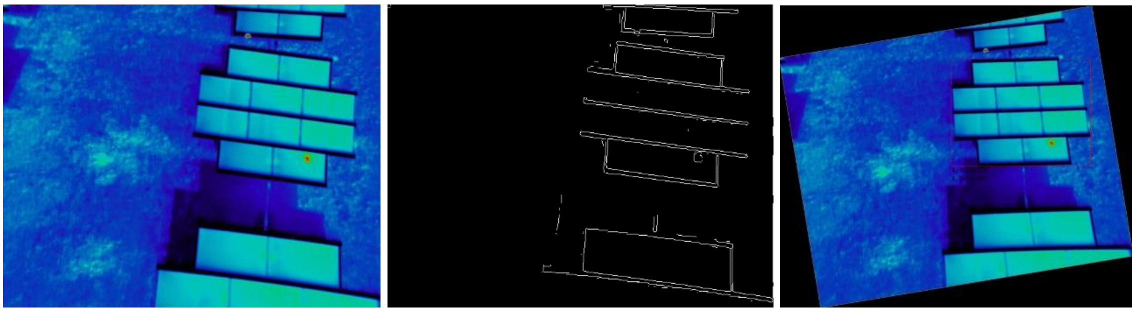

Figure 7. Input image (Left); edge detection (Middle); rotated image (Right)

The images can be inputted in the R-CNN panel detector when the images are properly oriented. There are several pretrained networks suitable to current object detection, such as AlexNet or GoogleNet, but they are not convenient for this work.

The method provides two values: The first value is the confidence level of each detected element. The second value is the location of the boundary box that contains the detected image. Figure 8 shows an example of an output of the detector.

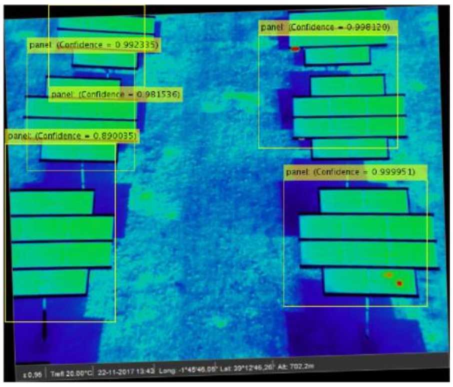

Figure 8. Output of pretrained R-CNN detector

The R-CNN hot spot detector can be employed when the panel ROIs has been identified. The hot spot detector is focused on the stablished boundary boxes. Hot spots outside the boundary boxes can be related to reflections, stones, or other undesired elements, so that they must be discarded. Only hot spots inside the boundary boxes will be considered. Figure 9 shows the outcome of the detector when Figure 8 is used as an input. A final image is provided including the telemetry data when the data has been analyzed. A new frame is inserted in the R-CNN detector in case of negative detection. The telemetry is associated with the hot spot in order to identify the panel when the R-CNN detector provides a defective spot.

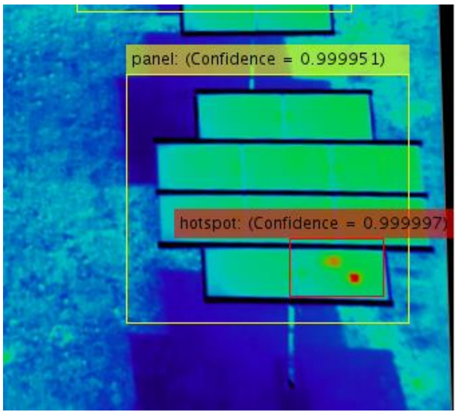

Figure 9. Result of hot spot detection

c) Results

The last report considers the results of both detectors and telemetry dataset. The GPS position is combined with the altitude, the UAV orientation, the camera angle and the focus angle. The method can ubicate the area of interest with these five variables, that corresponds with the complete image frame. It is important to distinguish between the ROIs and the areas of interest. The area of interest is the real area that is recorded in a specific frame, and the ROIs is a region of the frame that will be analyzed. The final report is a table with two rows. The first row provides the GPS information, and the second row provides the coordinates of the area of interest. The results may be seriously affected if the telemetry dataset are not accurate. Figure 10 shows an example of the final results of the processing of Figure 9, where the telemetry information has been associated with the hot spot.

	GPS Latitude/Longitude	Hot Spot
Frame 1	-1.7629 / 39.2131	535/381/71/44

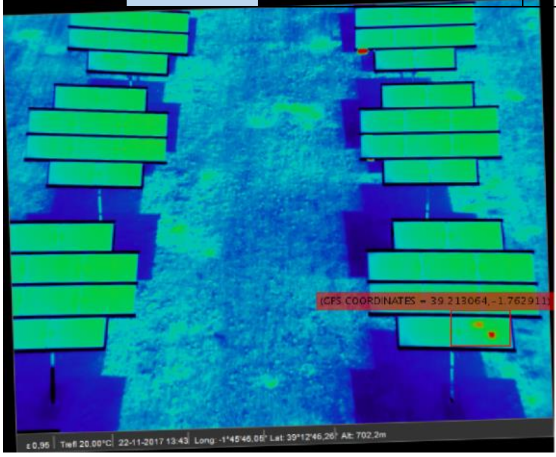

Figure 100. Hot spot and GPS ubication. Combination of IR image and telemetry

Finally, the plant operators can verify the results in the solar plant with handheld thermographic cameras and GPS. However, the proposed technique facilitates their job, especially in large plants with several thousand of panels installed.

4. Conclusions

This paper proposes a novel method to identify faults in solar panels from data provided by a condition monitoring system embarked in an unmanned aircraft vehicle. This system can inspect large solar plants, with thousands of solar panels, reducing the time and the costs of the thermographic inspections. The data acquisition of these modern systems requires new efficient algorithms to be processed. This paper proposes an autonomous hot spot detector based in recurrent convolutional neural network. The detector is created by three main stages: training process; data acquisition and processing, and; results. The detector identifies panels with different shapes and hot spots. This information is studied together with the telemetry data when the hot spots are identified. The outcome of the detector is the real position of a hot spot within the solar power plant. The detector has demonstrated to be highly accurate in detecting the hot spots. A further difficulty encountered is the accuracy of the hot spot ubication. An small error in telemetry parameters such as altitude, orientation, camera angle, focus angle or GPS position, could return an inaccurate ubication of the hotspots. The number of images utilized to pretrain the net is suggested to be increased in future works to improve the accuracy the detector. The detector will be also trained to distinguish between different types of hot spots through a pattern recognition tool.

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