Innovative Automated Control System for PV Fields Inspection and Remote Control

Mohammadreza Aghaei, *Student Member, IEEE*, Francesco Grimaccia, *Member, IEEE*, Carlo A. Gonano, and Sonia Leva, *Senior Member, IEEE*

***Abstract*— Unmanned Aerial Vehicles (UAVs) are becoming a reliable and useful instrument in monitoring and diagnostic services in the energy field. Operation and maintenance is a crucial factor for PV plant inspection and control activities which currently are quite hard to be performed due to manual and dispersive procedures. The automation of the monitoring techniques will become in future an essential task in this market and Unmanned Aerial System (UAS) technology can play a role in it. This paper proposes a novel, comprehensive and innovative approach in order to automate the inspection and prognostic procedure by means of designing a control system in order to provide accurate information on operating conditions of PV plants. The system is able to perform PV systems' monitoring, diagnosis, defects and failures reconnaissance, data processing and to propose remedial actions. In current experimental research, only IR sensor imaging was examined to evaluate thermographic behavior of the PV modules and to build the related image processing algorithm. However, it is possible to easily extend such a procedure in order to manage a larger amount of data. First results of this work have proven that the proposed procedure is very promising being fast, cost effective and adaptable to large PV plants which can be controlled during their entire lifetime.**

***Index Terms*— UAVs (Unmanned Aerial Vehicles), PV system diagnosis, Control systems, Automated IR analysis, image processing, PV plant monitoring.**

I. INTRODUCTION

In the last two decades a growing interest in generating electricity by using renewable energy sources (RES) have been observed. In recent years, the implementation of PV plants expanded due to various merit aspects of using solar energy besides the generous government subsidies.

However, the access to reliable information about PV systems in terms of technical, design, planning and monitoring data in operating conditions leads to develop control techniques useful to their prognosis and evaluation of future energy performance.

Typically there are various tests to recognize the defects and failures on the PV modules or cells. In fact most of the defects and failures are related to intrinsic properties of cells fabrication process [1].

However, the scientists and researchers are exploring reasons and occurring mechanism of these defects and failures on modules in order to improve also reliability of inspection methods. One of the main factors for reducing the costs of PV systems is to enhance the lifetime of the PV modules. For this purpose, the first stage of the analysis is to understand the failures and degradations' characteristics on the modules their selves.

Therefore, accurate measuring and monitoring methods are required to identify PV module's failures in outdoor applications [2]. Furthermore, fast detection of PV module failures can guarantee to extend PV system lifetime and performance [3], [4].

In many countries outside Europe great financial sources are still invested on PV plants projects by both private and governmental corporations. Therefore, productivity and profits must be assured in the market over the entire PV plant life. The inspection of PV plants by UAS technology is a quite novel application to detect PV modules status and failures. There is still scarce information in this research area and more efforts are needed to develop innovative and effective inspection methods. In addition, the best way to make them cost effective and reliable, is to expand practical investigation monitoring various aspects of PV systems by UAVs. In fact, there is a large potential of this novel inspection technology in solar energy equipment which can be further explored by researchers [5], [6].

Traditional visual monitoring process of PV system was dependent just on human capabilities. This responsibility was always repetitive and boring for the inspector, and most of the time was affected by error in recognizing origin of PV systems' failures. In general, the usual inspection methods require long time to be performed. Moreover, current methods of PV inspection are not able to provide on-line information about failures in the monitored plants and most of them use quite time just for the data acquisition task without further analysis steps. On the contrary, the UAVs can carry out the

Manuscript received February 5, 2015; revised May 5, 2015 and June 16, 2015; accepted August 6, 2015.

M. Aghaei is with the Politecnico di Milano, Milano, 20133 ITALY (phone: +39-02-2399-3709; fax: +39-02-2399-8566; e-mail: mohammadreza.aghaei@polimi.it).

F. Grimaccia is with the Politecnico di Milano, Milano, 20133 ITALY (e-mail: francesco.grimaccia@polimi.it).

C. A. Gonano is with the Politecnico di Milano, Milano, 20133 ITALY (e-mail: carloandrea.gonano@polimi.it).

S. Leva is with the Politecnico di Milano, Milano, 20133 ITALY (e-mail: sonia.leva@polimi.it).

defect detection of modules in shorter time due to their large area coverage, high flexibility, light weight and high speed [7].

In this experimental research, an innovative and complete system is suggested to fill the gap between data collection of PV plant, data processing, post-processing analysis and final decision making. In this light, the inspection approach is represented by an automated system designed to integrate the whole steps of inspection in a near real-time monitoring procedure for small and large scale PV plants' maintenance operations. Furthermore an image processing technique has been used in this monitoring system to automatically recognize specific modules with defects or failures, since image processing techniques can provide precise information about degradation of PV modules [8]. Section II reports typical methods for failure detection, Section III explains the core procedure here proposed, while Section IV and V report first experimental results drawing relative conclusion.

II. Typical Methods for Defects and Failures Detection on PV Modules

Generally, any effect on PV module which decreases the performance of the module, or even influences on the module characteristics, is considered as a failure. Whereas, a defect can be defined as an unexpected or unusual thing which has not been observed before on the module. However, defects often are not the cause of power losses in the PV fields [5].

There are many different diagnosis tools and methods to explore the defects and failures on the PV modules (e.g. I-V characteristics, visual inspection, thermographic analysis and photoluminescence) [9].

Recently other new methods like electroluminescence and UltraViolet (UV) fluorescence techniques have become more interesting for detection of PV modules' defects and failures which consequently cause decrease in the revenue of PV plant owners. Investigation about novel monitoring methods is again a crucial issue in the solar energy market growth [10].

A. Visual Assessment

The first step of the PV module monitoring is inspection by sight. The visual assessment is a very simple method to detect some failures or defects. In fact, visual monitoring allows to observe the most external stresses on the PV modules. In addition, this method can give an overview of PV systems condition. The most visible defects and failures are bubbles, delamination, yellowing, browning, bended, breakage, burned, oxidized, scratched, broken or cracked cells, corrosion, discoloring, anti-reflection, misaligned, loose, brittle fracture and detachment. Visual assessment should be carried out before and after module's installation to evaluate effect percentage of electrical, mechanical and environmental stresses on the PV module [11].

B. Thermographic Assessment

Thermographic inspection is a popular method that can provide enriched data about PV module status. Typically, it is carried out by infrared radiation (IR) imaging sensor. Thermal vision assessment is a harmless and contactless monitoring technique and it can diagnose some of the defects and failures on the PV modules. Furthermore, this method can be performed during normal operation of PV systems and it does not need to shut down the plant. The main task of thermographic measurement is to find the defects or failures under temperature distribution of module surface [10]. Generally, the IR imaging camera works in a wavelength range between 8 and 14 µm, and test procedure must be performed in low external temperature, wind and under clear sky with at least irradiation of 700 W/m^2 on the modules. It should be taken into account that during the measurement test, the inspector must be aware about reflection, shadowing and self-radiation of sensor. The best position of IR imaging camera is in a perpendicular position with respect to the target module [12], [13]. Commonly, the thermographic assessment is carried out to identify open circuited modules, bypass diode problem, internal short circuits, potential induced degradation, delamination, complete or partial shadowing, invisible cracks or micro-cracks, broken cell and hot spots [14], [15].

C. PV Parameter Performance Assessment

The main measurement parameters of PV modules is comprised of open-circuit voltage, short-circuit current, fill factor and maximum power point. I-V measurement curve gives sufficient information about PV module condition. Normally, the I-V curves are measured under standard test condition (Cell temperature = 25°C, Irradiance=1000 W/m^2, spectral distribution of irradiance air mass=1.5, wind speed=0 m/s) they can be used as an ideal reference for comparison of the PV modules in different conditions [16].

Series and shunt resistances (R_s, R_{sh}) can have influence on the slope of I-V characteristics and other parameters of PV module. With this regards, values of R_s and R_{sh} can be extracted from steep slope of I-V curve on the open-circuit voltage (V_{oc}) and short-circuit current (I_{sc}). Therefore, I-V characteristic behavior of the module depends on variations of R_s and R_{sh} [17].

D. Photoluminescence, Electroluminescence and UV Fluorescence Techniques

Photoluminescence (PL) and Electroluminescence (EL) are recent measurement methods which evaluates PV modules by luminescence images. In fact, the PL and EL measure the irradiative recombination of photons since carriers are excited into the solar cells. In PL technique [9], the carriers are generated by light, and then they are accumulated in defects or impurities parts of cell region. Therefore, the luminous regions present higher minority carriers and dark regions show the defect concentration on the solar cell. EL is very similar to PL technique with the difference that the carriers are injected to the solar cell junctions using an applied voltage in forward bias [18], [19].

Initially, UV fluorescence (FL) imaging technique was performed to detect EVA (Ethylene Vinyl Acetate) degradation. The most common reason is due to the UV light of solar irradiation, it decomposes the PV modules' encapsulant. In this technique, the emission spectrum can be received from a scanning of the specific excitation wavelength less than 350 nm, later on the same way is done for a specific fluorescent wavelength of the excitation light.

However, all of these measurement tests are non-destructive methods for PV module monitoring [20].

III. Method and Experimental Setup

The performance analysis of a PV-plant, with the aim of identifying and recognizing defects or failures, can be achieved by using electrical measurements (voltage, current, power and energy), visual inspection and thermographic analysis during normal operation. All these retrieved data together with captured images have to be linked to weather conditions and other external conditions such as shading, service interruption due to maintenance activities, and so on.

Regarding the electrical measurements, there are many monitoring systems now used in medium-large size PV power plant (nominal power higher than 100kW). Such systems can give us useful information about general performance of the PV plant, detailed information about the working status of inverters, transformers, PV arrays and switches [21]. On the other hand, these systems are not able to detect problems related to single module faults and sometimes neither to a series of modules. The visual and IR analysis instead can be referred to a single component and in particular to the single PV module. Nevertheless, manned inspection usually takes time and the data analysis complexity naturally increases with the PV system size.

In this research, a novel method has been developed in order to set up an integrated inspection system for PV plants. Such a system is able to perform detection, recognition, analysis and post-processing of various defects and failures on modules in short time and as well, it is able to provide reliable and accurate information of PV plant condition on-line. In this regards, UAV platform [22] was employed to monitor PV modules conditions by using special visual and thermography sensors mounted on the UAV to scan the defects and failures and send them to the ground center station for analysis. In the following sections particular attention is focused both on IR analysis and the automatic procedure set up.

A. Novel Approach Description

Punctual inspection of PV systems leads to identify defects and failures related to module degradation. Briefly, rapidity of monitoring procedures can prevent to waste time in the recognizing and analyzing defects and consequently, it leads to propose an effective solution for PV field operators.

Fig. 1 illustrates a schematic view of the proposed system for the monitoring of the PV plants using UAV technology. The proposed smart monitoring system is used to explore the defects or failures on PV modules and it can propose an appropriate solution for each affected PV module. In this concept, the monitoring system is integrated with inspection, recognition of the problem, processing and decision making. Therefore, all the requirements for operation and maintenance are associated in such a system.

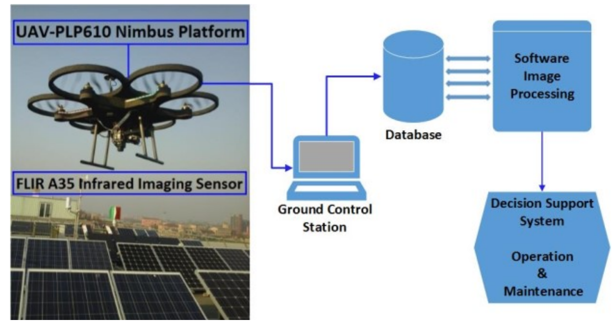


Fig. 1. Schematic of the smart monitoring system for PV plants.

As it is shown in Fig. 1, the thermographic assessment is carried out by mounted infrared imaging sensor on the UAV. Then, automatically the images captured are transferred to the Ground Control Station (GCS) by RF channel. Later on the classified data are sent by the GCS to the database for the following processing.

After software analysis of the received images, all the processed information are transferred to the decision support system for appropriate future actions to be taken. In this phase, the system evaluates the information in order to detect the specific defect or failure on the PV modules. Regarding to this identification, the decision support system propose the best solution for particular affected PV module, according to the specific strategy implemented by the O&M service.

In the database, there are comprehensive information about PV modules condition based on the previous experimental tests and datasheets. Therefore, this smart monitoring system can perceive the characteristics of all of the PV module's defects or failures and track them during time.

All these procedures can be performed in parallel hence entire inspection of PV systems can be accomplished in few hours also for a large plant.

The capability of this automated inspection system is higher than the human inspector and other traditional methods. The time duration of monitoring procedure and decision making for the proper solution is faster than previous inspection methods and the system can provide a reliable information for owner of PV plant in very short time. Accuracy of the system is high and it can identify not only defects or failures but also location of the specific degraded module in the PV plant since images captured by the UAV have GPS metadata inside. The system can record all the monitoring information related to the PV module failures on the database for future actions based on the history of the plant, its track-record and current performance. Moreover, the system is compatible with other common methods for defects and failure detection, not only IR (e.g. visual assessment, thermographic analysis, etc.).

B. Image processing application in PV module monitoring

Digital Image Processing (DIP) technique is commonly used in fields of electrical and computer engineering. In fact, it is possible to apply image processing on analog and optical areas. Typically, input of image processing is an image taken from video frames or other photographs but the output of image processing technique is not just an image, it can be also a group of some parameters or characteristics data related to primary image. Fundamentally, digital image processing is defined as the use of computer algorithms to apply image processing techniques on the digital image or video frames and it can be useful also in PV system applications [23].

The main task of image processing techniques is to treat the images by applying proper signal processing techniques [24].

Digital images and videos from visible light and IR to gamma rays and beyond are used in thousands of industrial applications. The digital image processing is the ability to process these images as signals, in order to manage information for many reasons like, for example, removal of degradation, enhancement, compression, and so on. It is beyond the scope of this paper explain in depth fundamentals of this discipline which deal with the mathematical framework to describe and analyze such images as two or three-dimensional signals in the spatial, spatio-temporal, or frequency domains.

Many DIP techniques based on the EM spectrum have been developed. Linear translation, convolution, 2D and 3D Fourier transform [25], noise filtering, edge detection, sparsity-based and others [26], but her we use.

Thus image processing is a useful tool to distinguish the defective parts from the healthy ones on the PV modules. Image processing is used not only for defects' or failures' detection on the PV modules, but it is helpful to determine also degradation percentage of affected modules and as well classifying the specific defects or failures. Obviously, only a sufficient number of pixels can give us reliable data about PV module status, so the use of appropriate sensors is mandatory. In this research, the captured infrared pictures of the PV modules were analyzed by image processing technique. Initially, the thermography images were filtered using some filters in Matlab environment [27], [28].

Fig. 2 illustrates the procedure of defect detection on the PV modules. In the proposed algorithm, the first step is devoted to transform the color images into grayscale images since the latter is clearer than the original one. This step is carried out in order to determine the luminance on the PV module surface. In the digital color image each pixel is characterized by three bytes which are associated with luminance of the main basic colors (Red, Green, and Blue). The grays are defined instead in the interval range [0; 255], 0 for black and 255 for white areas, thus the luminance of a pixel is usually described by 1 single Byte which correspond to 256 levels [29].

Later on, the image needs to be smoothed and noise effect should be eliminated (e.g. due to smear/dust or other dirties on the PV modules related to outdoor environment). Therefore, the images should be filtered to eliminate or decrease the noises' effect of different elements on the images, following different steps:

1) *Grayscale.* The gray scale picture is read in digital format: hence the luminance of each pixel is saved in a matrix.

2) *Spectrum in Fourier.* The picture's "spectrum" is calculated by mean of the 2D Fast Fourier Transform (FFT). In the space domain, applying a filter *h(x,y)* to a function *f(x,y)* corresponds to the convolution:

$$f_{FILT}(x,y) = \iint h(x-x', y-y')\, f(x',y')\, dx'dy' \tag{1}$$

In the Fourier domain, instead, it is sufficient to multiply together the spectra $H(k_x, k_y)$ and $F(k_x, k_y)$ respectively:

$$F_{FILT}(k_x,k_y) = H(k_x,k_y)\cdot F(k_x,k_y) \tag{2}$$

where k_x and k_y are the wavenumbers for the directions x and y. Usually this operation is much faster than calculating the convolution in the space domain.

3) *Filtering function.* A filter function is applied to the picture's spectrum in the Fourier domain (also known as "wavevector domain" for spatial transformation).

In the follows we report synthetically the expression of some filter functions in the 2D Spatial Fourier domain.

– Gaussian filter:

$$H\left(k_x,k_y\right) = \exp\left(-\frac{1}{2}\left(\frac{k_x^2}{k_{0x}^2}+\frac{k_y^2}{k_{0y}^2}\right)\right) \tag{3}$$

– Rectangular Average filter:

$$H\left(k_x,k_y\right) = \frac{\sin(\pi k_x / k_{0x})}{(\pi k_x / k_{0x})}\cdot\frac{\sin(\pi k_y / k_{0y})}{(\pi k_y / k_{0y})} \tag{4}$$

– Rectangular Ideal filter:

$$H\left(k_x,k_y\right) = \left(|k_x| < k_{0x}\right)\cdot\left(|k_y| < k_{0y}\right) \tag{5}$$

where k_{0x}, k_{0y} are arbitrary parameters: conceptually they correspond to the inverse of the cut-lengths for the filter. If k_{0x} and k_{0y} are small, the image will be strongly smoothed since high frequency components will be reduced.

4) *Anti-transforming.* The filtered spectrum is anti-transformed back from the Fourier domain. The final result is the filtered image.

The filtering step can eliminate certain noise effects but it may cause blurred vision on the edge of image. Gaussian filter helps to reduce the image sharpening, decrease noises and also it can highlight the boundaries of PV panels in order to make easier the number of panels' recognition for counting and statistical evaluation of data.

In the defects detection procedure, the most crucial issue is to specify the average luminance and threshold in terms of the number of standard deviation. Nevertheless, both steps which involve filtering and estimation of stains luminance can be performed in parallel. In general, hot spot, white spot, cracks and other defects influence the temperature of PV modules' surface. Therefore, affected PV modules do not have uniform thermal surface. Thus, using a typical binary method to distinguish defective regions from healthy parts, the image is separated in black and white areas. The luminance of hot portions are higher than the cold portions, which are indicated by 1 (white) and 0 (black) respectively.

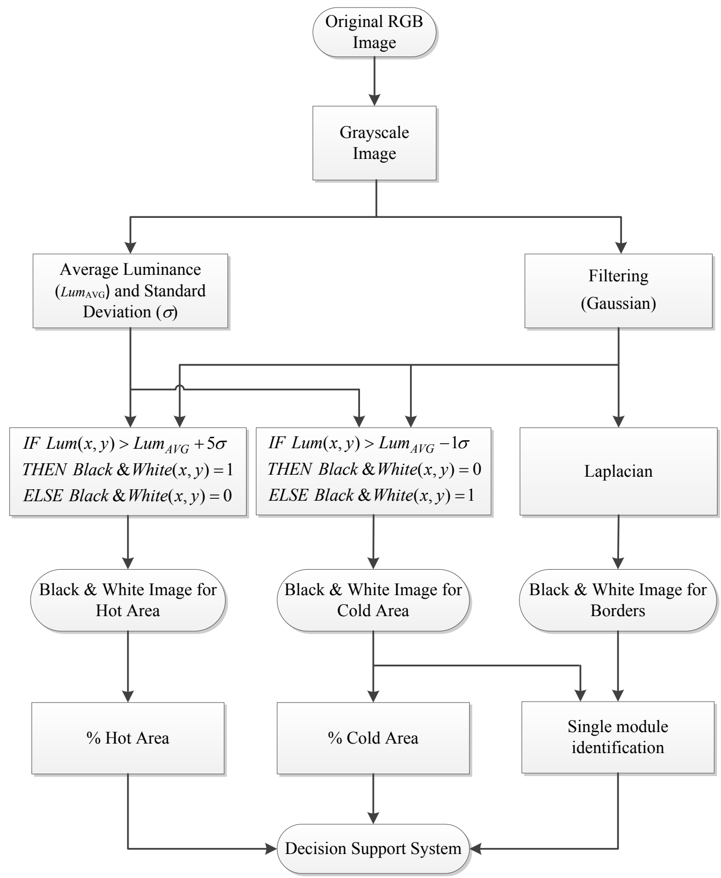


Fig. 2. Algorithm of defect and failure reconnaissance in PV module.

In fact, binary image [25] is one of the basic methods for region segmentation in the image processing. Thus, stain and normal parts of images can be separated to white and black completely. It distinguishes the image to 0 and 1 divisions. In addition, it senses the threshold value of stained parts as significant zones from the total image area. With this process it is easier to automatically evaluate the spot/defect areas (typical shape and extension) and to make possible first hypothesis on the defect categorization.

In this step (see again Fig. 2), if the luminance (*Lum*) of white stains is five standard deviation higher than average luminance (Lum_{AVG}), then that part of the module has some defects. The other part of the module is healthy.

Black and white images for hot areas are defined as follow:

$$\begin{aligned} &IF\ Lum(x,y) > Lum_{AVG} + 5\sigma \\ &THEN\ Black\ \&\ White(x,y) = 1 \\ &ELSE\ Black\ \&\ White(x,y) = 0 \end{aligned} \tag{6}$$

While black and white images for cold areas are also defined as follow:

$$\begin{aligned} &IF\ Lum(x,y) > Lum_{AVG} - 1\sigma \\ &THEN\ Black\ \&\ White(x,y) = 0 \\ &ELSE\ Black\ \&\ White(x,y) = 1 \end{aligned} \tag{7}$$

In this experimental test, the chosen value of luminance was just computed based on trial and error method. It means that many different pictures were examined in order to obtain the best luminance value for identification of defects on the modules.

It should be noted that the 5σ and -1σ thresholds were found through a heuristic procedure: we compared different groups of pictures, distinguishing among those containing either healthy modules or defective ones. We then calculated the statistical indices and luminance distribution for each pictures, observing that for defective modules the distributions have *fat tails* for luminance major than 5σ over the average (see Fig. 3). We should highlight that 5σ is not a definitive value; in fact it could depend on the characteristics of the IR camera used to shoot the pictures. Moreover, luminance distributions for different pictures can have quite variable shapes, depending on which objects are actually shown in the image, for example see Fig. 3a and 3b, related to the images reported in Fig. 4a and 4b respectively. The second picture (Fig. 3b) shows a more Gaussian distribution since it contains just PV modules (no grass inside) with a roughly mono-modal luminance behavior. On the contrary Fig. 3a presents a more heterogeneous content due to the presence of terrain elements in a relevant part of the picture; thus, as shown, this sort of terrain sideband significantly modifies the average luminance distribution beyond five standard deviations. However, as long as we could test, the 5σ-threshold criteria revealed to be practical and robust in order to detect defective areas.

The area of the defective portion gives some indications on the reliability of the PV module. In fact, it is an index to

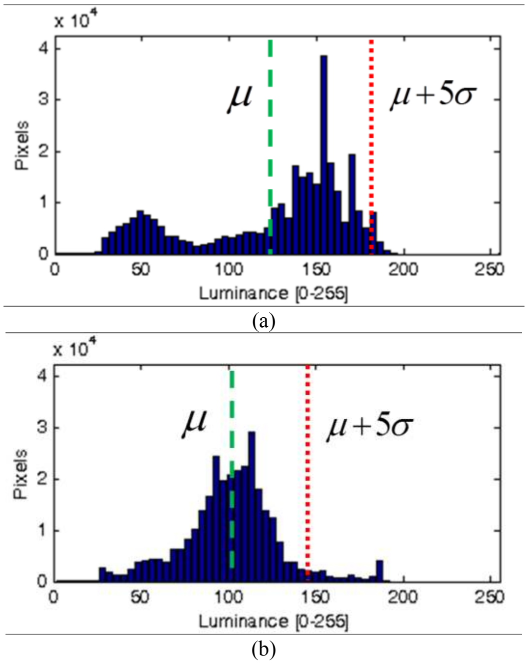


Fig. 3. Example of luminance distribution for two different modules: (a) a healthy module and (b) a defective module. In the histograms, the average μ (green dashed line) and the upper threshold $\mu + 5\sigma$ (red pointed line) are shown.

clarify rate of degradation. The damage percentage of PV module is calculated from the equation below:

$$\%Degradation = \frac{White\_area}{Total\_Area(PV\_Module)} \cdot 100 \tag{8}$$

According to our estimation, as better explained later on in Section IV, if the damage percentage is higher than 5% then the module is affected by some defects and it needs deeply investigation. This degradation percentage threshold is obtained with many trials and errors on the different PV modules and fields.

The last part of the procedure is based on the Laplace model. It is useful, in particular, to highlight the border of modules [25] in order to count number of monitored modules. Instead of the other filters previously mentioned, the Laplace operator acts locally with no need for convolutions, and its general expression is:

$$L(x,y) = \nabla^2 f(x,y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \tag{9}$$

In a discrete 2D space the Laplacian of a function *f(x,y)* can be calculated directly on a point (x_i, y_j) as:

$$L(x_i, y_j) = \frac{f_{i+1,j} + f_{i-1,j} - 2f_{i,j}}{\Delta x^2} + \frac{f_{i,j+1} + f_{i,j-1} - 2f_{i,j}}{\Delta y^2} \tag{10}$$

where Δx and Δy are the pixel's sizes (usually they are set equal to 1), while $f_{i,j} = f(x_i, y_j)$ is the function's value calculated on point (x_i, y_j).

It should be noted that the Laplace operator is not sensible to the absolute luminance, but to its rapid variation, so it can be used to detect the contours of the objects inside the image. However, it is also sensible to high frequency noise, so the picture should be filtered first.

After image analyses, all the information are transferred to the decision support center in order to evaluate the defect and failure kind, then proposing the best solution for the specific plant, comparing actual performance and its monitored history. The recognition of the defect is finally confirmed in the decision support center by comparison with previous measurements and datasheet stored in the database.

IV. Experimental Analysis and Results

In this research, a thermographic assessment has been performed for PV modules in SolarTech Lab using mounted IR imaging camera (FLIR A35) on a light UAV (PLP610 Nimbus platform). The main features of the used UAV are reported in [5], furthermore it can operate at constant wind speed of 5 m/s, up to 10 m/s of wind gusts and light rain condition.

The following Table I indicates the technical specification of the IR imaging camera.

TABLE I
The IR-Imaging Camera Properties

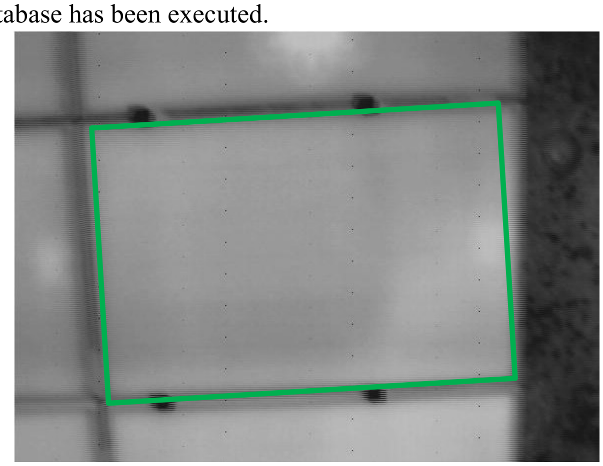
Imaging & Optical Data	Description
IR resolution	320 x 256 pixels
Spatial resolution (IFOV)	48° (H) x 39° (V) with 9 mm lens 25° (H) x 19° (V) with 19 mm lens. Lenses are not interchangeable and need to be specified at time of order.
Object temperature range	-25°C to +135°C (-13 to 275°F) / –40°C to +550°C (-40 to 1022°F)
Thermal sensitivity/NETD	< 0.05°C @ +30°C (+86°F) / 50 mK

In this experimental test, it should be considered that identification of defects is not directly dependent to spatial resolution of the IR sensor since the UAS flies at different altitudes in order to recognize defects with various dimensions. In addition, the best Noise Equivalent Temperature Difference (NETD) of IR imaging camera was recorded between 30mK and 40mK in order to display the IR images in high quality and to emphasize failures on modules. In the performed experimental test, the emissivity (ε) was set to 0.85 based on the surface characteristic of modules [28, 29].

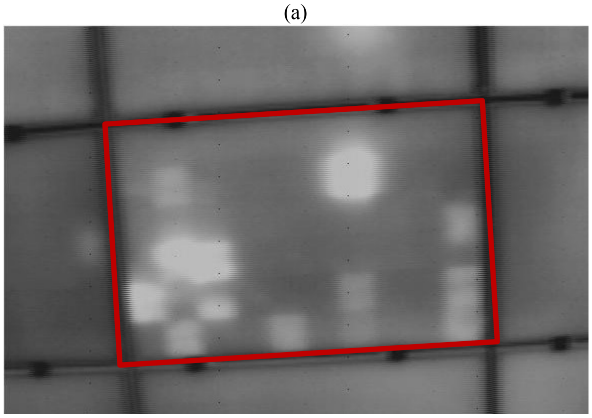
In accordance with the proposed automated system, the images captured by the thermal camera mounted on-board, are sent to the ground control station and then transferred to an ad-hoc PC for further analysis with the described algorithm. At this stage the GCS responsible for UAV flight control has not yet been modified for this particular experiment. However it is trivial to conceive an additional processing unit to be added to GCS, without compromise the control functionality, and thus not interfering with legal procedure to obtain Permit to Fly certification by the civil Aviation Authority (e.g. ENAC for the Italian case).

In this regards, the images are processed by means of the program described in Section III to recognize defects and failures of the PV modules. Later on the processed images are transferred to the decision support center (the PV laboratory in our experiment) where production data are available in order to be able to perform further evaluation and correction action, or propose intervention if required.

The inspection has been performed by the proposed smart system which is able to automatically recognize affected PV modules which require more accurate analysis in SolarTech Lab or an equivalent center. All the affected modules has been thus identified and can be sent to the decision support center. In our view in fact if the module presents a serious percentage of degradation (e.g. >5%) it needs further investigation: the module should be first analyzed directly on site where technicians can try to recover some kind of faults (e.g. bypass diode, misconnections, etc.) and – if required - replace or send to the laboratory for a more in depth tests. Furthermore, we can decide of course to set different alert thresholds, for example between 3 and 5%, to tag the module as "keep it under control" increasing burden for the overall procedure. Nevertheless, if the O&M is performed over time, the smart inspection system does not consider a defect or a failure for a specific module before a previous comparison in the historic database has been executed.



(a)



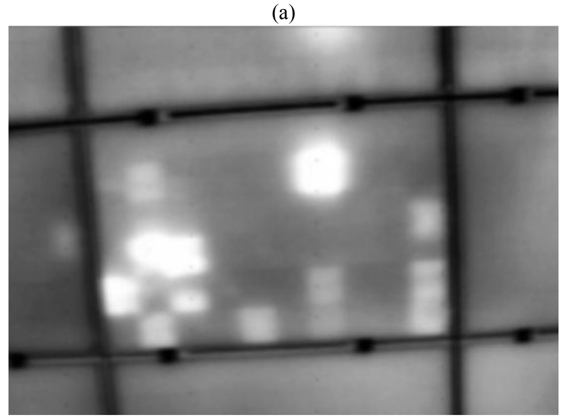
(b)

Fig. 4. Original images of (a) a healthy module sample and (b) a recognized defective module sample.

In the present first experimental work, we have selected only a few samples among all the obtained results to demonstrate the capability and reliability of this automated remote inspection system.

For comparison, the selected samples were chosen based on their conditions. One of this modules is faulty while the other module is a healthy one. In addition, it should be taken into account that the original image of healthy module sample is brighter that the affected module due to the high irradiation of sunlight during the inspection procedure and also position of sensor toward the module. The original images of the affected and healthy PV module are shown in Fig. 4.

(a)



(b)

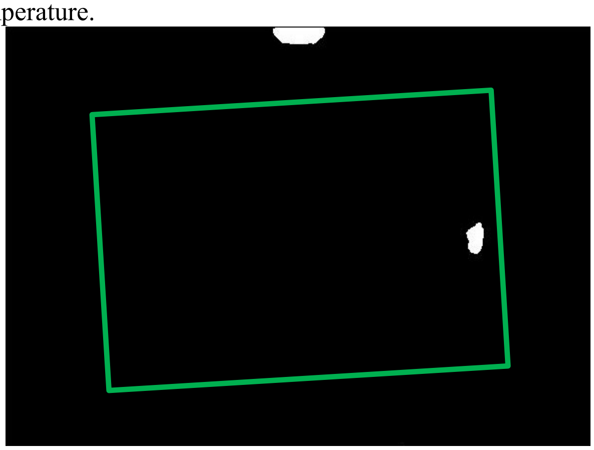
Fig. 5. Filtered images of (a) a healthy module sample (b) a defective module sample.

The images then have been transformed to grayscale, as already explained, and the filtering lead to improve quality of images making the image smoothed. Moreover, it enhances the quality of white areas (stains) on the images making the reconnaissance operation of defects facilitated. In this intelligent monitoring system, the Gaussian filter have been used to eliminate a certain impact of noise in the images. The filtered images of affected and healthy modules are reported in Fig. 5.

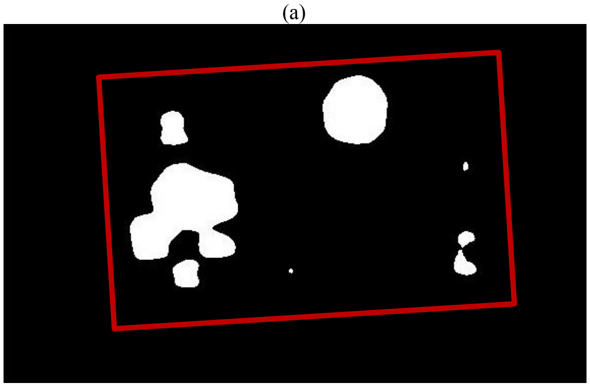
The binary images obtained by the method described in Section III are illustrated in Fig. 6.

In Fig. 6b, the parts affected by defect or degradation appear as white areas on the PV modules whereas the black areas represent the normal parts without any problem.

Fig. 6a shows the image of a healthy module. It should be noticed that the white stain part located on top of the image in Fig. 6a is due to the reflection of sunlight (it can be seen from the daylight image) and the other white stain is related to junction box of PV module which has a normal higher temperature.



(a)



(b)

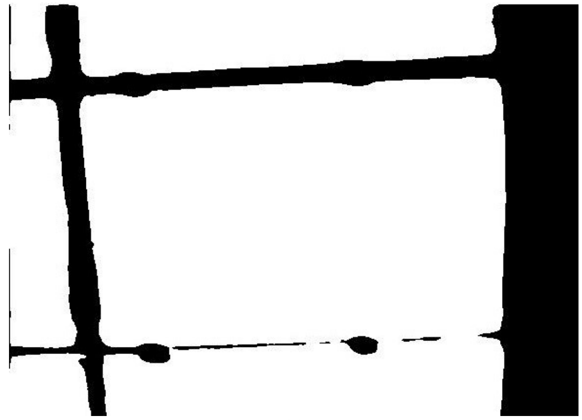
Fig. 6. Binary Images of (a) a healthy module sample and (b) a defective one.

This is why in the proposed method we decide to set a threshold at least higher than 3% to have an alert: in fact, we can consider the size of a junction box rather similar to one cell size. Furthermore in some cases in correspondence of the supporting structure IR sensors can detect additional differences in temperature [30], [31]. Therefore, the authors consider a reasonable threshold of 5% to avoid high rates of *false positives* in order to identify not all but almost every significant defect in the PV plant. A similar approach is proposed by [32], [33] where the authors classify the severity of faults in three different degrees, namely minor, medium and heavy faults. In this last case part of a module is typically shorted by a bypass diode as an outcome of, for examples, mismatch, cell cracking, partial shading, and increased internal resistance [8].

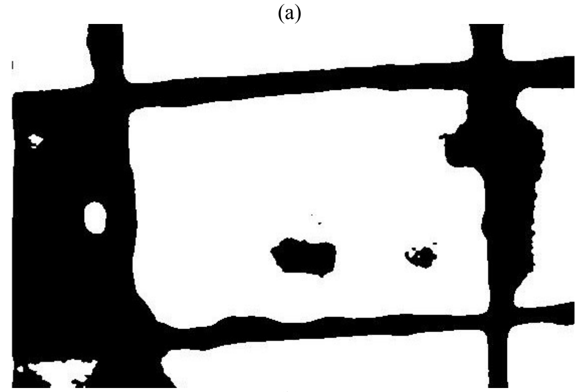
However it is not easy to find a direct correlations between the identified areas and the degradation of the module in terms of power, especially under working condition. Some very interesting reference value in this context can be found again [8].

Our threshold model determines the boundary areas of the PV module frames which can be used for recognizing frames problems. Threshold model of images of affected and healthy model is represented in Fig. 7.

As it can be seen from Fig. 7, the frames are indicated by black color which is colder than other areas of the module. The white color parts show warmer areas on the module (Fig. 7a) which is very uniform due to the integration of temperature on the module's surface. Whereas, in Fig. 7b the white parts with hotter temperature are more inhomogeneous.



(a)



(b)

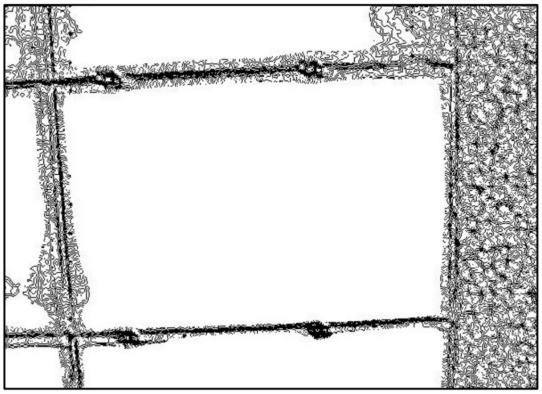
Fig. 7. Threshold Model of Binary images for (a) a healthy module sample and (b) a defective module sample.

Fig. 8 displays the final Laplace analysis of the images which were extracted from original images to represent a depth grasping of defect characteristics on the modules.

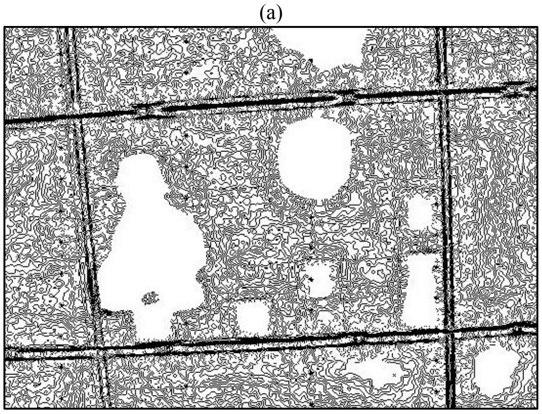
The Laplace model not only gives an overview of PV module condition, but also it can highlight the border of modules in order to count number of monitored modules. It is also useful for the monitoring system in aerial photography by UAV or to develop further services like mosaicking or photo mapping.

In the last step of this PV module monitoring system, as already mentioned, the entire of processed image data are transferred to the decision support center for further analysis based on multiple information (plant performance, data history, IR and visible pictures, electric data, previous maintenance reports, etc.). Decision makers realize for example that those stains on this specific PV module (Fig. 4b) are related to a shunt hot spot defect. Possible reason can be represented in that case by full or partial shading. In any case the system can suggest to use a bypass diode for affected cells to neutralize the impact of hot spot on the PV module. With regards to the previous experimental test for this specific module further solution can be recommended by the system.

In addition, this smart system is able to compute percentage of damage and degradation, statistics on number of affected panels out of the total number in the plant, and so on. According to equation (8), the calculated percentage of damaged area is equal to 15.8% for PV module shown in Fig. 8b which is higher than the minimum acceptable degradation range (5%), hence the module is considered in this case as faulty.



(a)



(b)

Fig. 8. Laplace analysis of (a) a healthy module sample (b) a defective module sample.

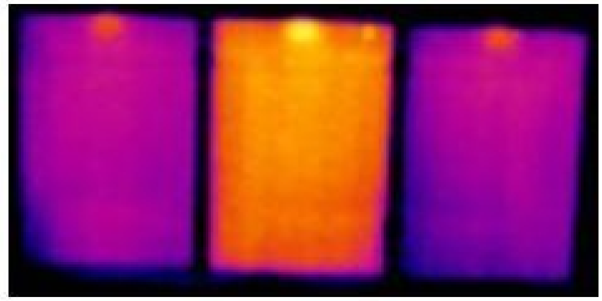
The here developed method can also be applied not to a single module, but to a general picture in which an array or a group of modules are present. In this case the procedure is also able to recognize part of a module shorted by a bypass diode and either an entire string or a single disconnected module, as shown in Fig. 9. In this case three modules are connected to the grid by means of three different micro-inverters [16]. One of these was out of order. According to equation (8), the calculated percentage of hot area is equal to 27.8% for the selected area shown in Fig. 9c, that in this specific case means one disconnected module out of three.

Finally, it is important to underline that the smallest defect which was detected in this test has a diameter of 0.6 cm; in any case it should be noticed that the smallest size of the detectable defect extremely depends on the flying height.

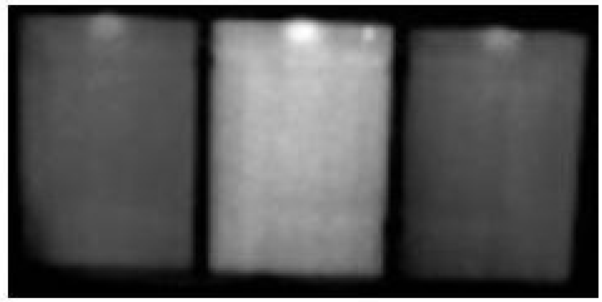
V. CONCLUSION

A growing demand of PV plant and modules in the energy market shows a high potential of the photovoltaic technology to meet the future energy quality requirements. Effective operation and maintenance can guarantee the PV system proper lifetime and payback for PV plants owner investment.

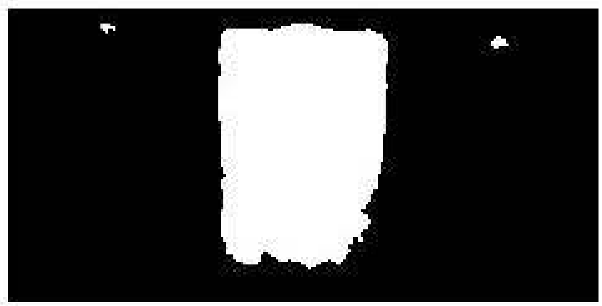
This manuscript was focused on design and pre-test an automated, integrated and smart system both for small and large scale PV plants inspection, to assess PV plant status and performance during its operational time.



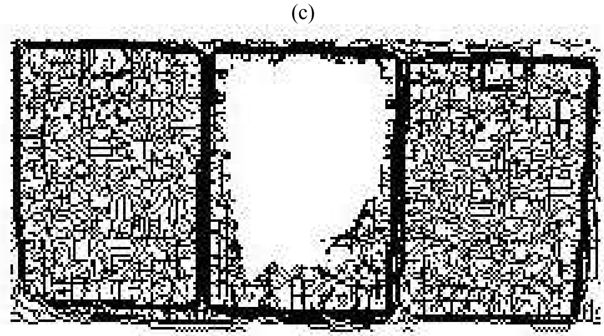
(a)



(b)



(c)



(d)

Fig. 9. The proposed method for the analysis of three modules in which a single module is disconnected. (a) Original picture (b) Grey scale picture (c) Binary picture (d) Laplace filtered picture.

In this innovative system, the images of PV modules are obtained by mounting IR and Visual cameras on UAV, which transfers the images to a processing unit for defect detection and post-processing. The image processing algorithm used in this experimental set up (in this paper only for IR) was a preliminary process to identify different problems and control opportunity, and further investigation is needed to develop a more complete, flexible and market oriented system in order to be implemented in advanced O&M services for PV plants.

REFERENCES

[1] M. Simon and E. L. Meyer, “Detection and analysis of hot-spot formation in solar cells”, *Solar Energy Materials and Solar Cells*, vol. 94, pp. 106-113, 2010.

[2] C. Paravalos, E. Koutroulis, V. Samoladas, T. Kerekes, D. Sera, R. Teodorescu, "Optimal Design of Photovoltaic Systems Using High Time-Resolution Meteorological Data," *IEEE Trans. Ind. Inform.*, vol. 10, no. 4, pp. 2270-2279, Nov. 2014.

[3] C. Ferrara and D. Philipp, “Why do PV modules fail?”, *Energy Procedia,* vol. 15, pp. 379–387, 2012.

[4] Z. Moradi-Shahrbabak, A. Tabesh, G.R. Yousefi, "Economical Design of Utility-Scale Photovoltaic Power Plants With Optimum Availability," *IEEE Trans. Ind. Electron.*, vol. 61, no. 7, pp. 3399-3406, July 2014.

[5] P. Bellezza Quater, F. Grimaccia, S. Leva, M. Mussetta, M. Aghaei, “Light Unmanned Aerial Vehicles (UAVs) for Cooperative Inspection of PV Plants”, *IEEE J. Photovolt.*, Vol. 4, n. 4, 2014, pp. 1107-1113.

[6] C. Buerhop, R. Weißmann, H. Scheuerpflug, R. Auer, and C. J. Brabec. “Quality control of PV-modules in the field using a remote-controlled drone with an infrared camera,” in *Proc. 27th European Photovoltaic Solar Energy Conference and Exhibition*, Frankfurt, Germany, pp. 3370-3373, 2012.

[7] F. Grimaccia, M. Aghaei, M. Mussetta, S. Leva, and P. B. Quater, “Planning for PV plant performance monitoring by means of unmanned aerial systems (UAS)", *Int. Journal of Energy and Environmental Engineering*, vol. 6, n. 1, pp. 47-54, 2014.

[8] X. Pengyun and L. Jigang, “Computer assistance image processing spores counting”, in *Proc. Int. Asia Conference on Informatics in Control, Automation and Robotics, CAR'09*, 2009, pp. 203-206.

[9] M. Munoz, M. Alonso-Garcia, N. Vela, and F. Chenlo, “Early degradation of silicon PV modules and guaranty conditions”, *Solar Energy*, vol. 85, pp. 2264-2274, 2011.

[10] C. Buerhop, D. Schlegel, M. Niess, C. Vodermayer, R. Weißmann, and C. Brabec, “Reliability of IR-imaging of PV-plants under operating conditions”, *Solar Energy Materials and Solar Cells*, vol. 107, pp. 154-164, 2012.

[11] F. Donatantonio, J. Fontchastagner, G. Petrone, G. Spagnuolo, J. Martin, and S. Pierfederici, “A PSO-Based Global MPPT Technique for Distributed PV Power Generation”, *IEEE Trans. Ind. Electron.*, pp. 1047-1058, 2014.

[12] M. Aghaei, P. Bellezza Quater, F. Grimaccia, S. Leva, M. Mussetta, “Unmanned Aerial Vehicles in Photovoltaic Systems Monitoring Applications”, in *Proc. 29th European Photovoltaic Solar Energy Conference and Exhibition*, Amsterdam (The Nederlands), pp. 2734-2739, 2014.

[13] J. Bachmann, C. Buerhop-Lutz, C. Deibel, I. Riedel, H. Hoppe, C. J. Brabec, et al., “Organic solar cells characterized by dark lock-in thermography”, *Solar Energy Materials and Solar Cells*, vol. 94, pp. 642-647, 2010.

[14] R. Ebner, B. Kubicek, and G. Újvári, “Non-destructive techniques for quality control of PV modules: infrared thermography, electro-and photoluminescence imaging”, *Proc. IECON*, 2013, pp. 8104-8109.

[15] S. Vergura, G. Acciani, O. Falcone, "A Finite-Element Approach to Analyze the Thermal Effect of Defects on Silicon-Based PV Cells," *IEEE Trans. Ind. Electron.*, vol. 59, no. 10, pp. 3860-3867, Oct. 2012.

[16] A. Dolara, S. Leva, G. Manzolini, and E. Ogliari, “Investigation on Performance Decay on Photovoltaic Modules: Snail Trails and Cell Microcracks”, *IEEE J. Photovolt.*, Vol. 4, pp. 1204-1211, 2014.

[17] M. Herman, M. Jankovec, and M. Topic, “Optimal IV curve scan time of solar cells and modules in light of irradiance level”, *Int. Journal of Photoenergy*, vol. 2012, 2012.

[18] T. Potthoff, K. Bothe, U. Eitner, D. Hinken, and M. Köntges, “Detection of the voltage distribution in photovoltaic modules by electroluminescence imaging", *Progress in Photovoltaics: Research and Applications*, vol. 18, pp. 100-106, 2010.

[19] R. Khatri, S. Agarwal, I. Saha, S. K. Singh, and B. Kumar, “Study on long term reliability of photo-voltaic modules and analysis of power degradation using accelerated aging tests and electroluminescence technique”, *Energy Procedia*, vol. 8, pp. 396-401, 2011.

[20] M. Köntges, S. Kajari-Schröder, and I. Kunze, “Cell cracks measured by UV fluorescence in the field”, in *Proc. 27th European Photovoltaic Solar Energy Conference*, 2012.

[21] W. Xiao, M.G.J. Lind, W.G. Dunford, A. Capel, "Real-Time Identification of Optimal Operating Points in Photovoltaic Power Systems," *IEEE Trans. Ind. Electron.*, vol. 53, no. 4, pp. 1017-1026, Aug. 2006.

[22] K. Nonami, “Prospect and recent research & development for civil use autonomous unmanned aircraft as UAV and MAV”, *Journal of system design and dynamics*, vol. 1, pp. 120-128, 2007.

[23] R. A. Mastromauro, M. Liserre, and A. Dell'Aquila, “Control issues in single-stage photovoltaic systems: MPPT, current and voltage control”, *IEEE Trans. Ind. Inform.*, vol. 8, pp. 241-254, 2012.

[24] G. Zhang, B. Li, B. Fu, L. Li, and G. Liu, “A comparative image analysis of discrete radial Fourier transforms”, *Optics and Lasers in Engineering*, vol. 48, pp. 1186-1192, 2010.

[25] C. Solomon, T. Breckon, *Fourier Transforms and Frequency-Domain Processing*. John Wiley & Sons, 2011.

[26] M. Petrou, C. Petrou, *Image Processing: The Fundamentals*. John Wiley & Sons, 2010.

[27] J. Schoukens, R. Pintelon, and H. Van Hamme, “The interpolated fast Fourier transform: a comparative study”, *IEEE Trans. Instrum. Meas.*, vol. 41, pp. 226-232, 1992.

[28] A. S. Nateri, F. Ebrahimi, and N. Sadeghzade, “Evaluation of yarn defects by image processing technique”, *Optik-International Journal for Light and Electron Optics*, vol. 125, pp. 5998-6002, 2014.

[29] J. C. Russ and R. P. Woods, “The image processing handbook”, *Journal of Computer Assisted Tomography*, vol. 19, pp. 979-981, 1995.

[30] G. Acciani, G. Simione, and S. Vergura, "Thermographic analysis of photovoltaic panels," in *Proc*. *Int. Conf. on Renewable Energies and Power Quality (ICREPQ’10)*, March, 2010, pp. 23-25.

[31] M. D. Bazilian, H. Kamalanathan, and D. Prasad, "Thermographic analysis of a building integrated photovoltaic system," *Renewable Energy*, vol. 26, pp. 449-461, 2002.

[32] Y. Hu, W. Cao, J. Ma, S. J. Finney, and D. Li, “Identifying PV module mismatch faults by a thermography-based temperature distribution analysis,” *IEEE Trans. Device Mater. Rel.*, vol. 14, no. 4, pp. 951-960, Dec. 2014.

[33] Y. Hu, W. Cao, J. Wu, B. Ji, “Thermography-Based Virtual MPPT Scheme for Improving PV Energy Efficiency at Partial Shading Conditions,” *IEEE Trans. Power Electron.*, vol. 29, no. 11, pp. 5667-5672, Nov. 2014.

Mohammadreza Aghaei (S’14) received the B.S. degree in Electronics Engineering from the Azad University, Iran, in 2008 and the M.S. degree in Electrical Engineering from the University Tenaga Nasional, Selangor, Malaysia, in 2013. Now he is Ph.D. student at the Politecnico di Milano. His research interests include power electronics, solar cells, photovoltaic systems, renewable sources and UAVs.

Francesco Grimaccia (M’07) received the M.S. in mechanical engineering in 2003 and Ph.D. (cum laude) in electrical engineering in 2007 from Politecnico di Milano, Italy. Currently, he is Assistant Professor in the Energy Department of Politecnico di Milano. His main research interests are related to soft computing techniques development and application in different fields, such as wireless sensor networks, UAS, photovoltaic and other energy harvesting technologies. Dr. Grimaccia is member of IEEE, CIS, SPIE and President of AEIT Young Engineers Society.

Carlo A. Gonano received the M.S. degree in Aeronautical Engineering from Politecnico di Milano, Italy, in 2011. Currently he is a Ph.D candidate in Electrical Engineering at Politecnico di Milano. His research interests range from Fluid-dynamics to the Theory of Relativity. His main research interests are related to image analysis, circuit models for Maxwell's equations, Evolutionary Algorithms and EM metamaterials and their paradoxes.

Sonia Leva (SM'13) received the M.S. and Ph.D. degrees in electrical engineering from Politecnico di Milano, Italy, in 1997 and 2001, respectively. Currently, she is Associate Professor of Electrical Engineering in the Energy Department of the same university. Her research interests include EMC, power quality, and renewable energy analysis and modeling. She is member of the Italian Standard Authority (CEI/CT82) and of the IEEE Working Group "Distributed Resources: Modeling & Analysis" and Task Force on "Modeling and Analysis of Electronically-Coupled Distributed Resources".