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FAST CURRENT MAPPING OF PHOTOVOLTAIC DEVICES USING COMPRESSIVE SAMPLING.

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Introductive summary

Spatial characterisation of the optical, electrical and material properties of photovoltaic (PV) devices is necessary for the development of new PV technologies and the optimisation of manufacturing methods. In this work, the recently developed compressed sensing (CS) sampling theory is applied to the Light Beam Induced Current (LBIC) measurement process in order to significantly reduce measurement time. The raster scanning process of the LBIC system is replaced with a Digital Micro-mirror Device (DMD) pattern projection system. Using this method, a full image of the device can be reconstructed from far fewer measurements by means of an optimisation algorithm. Approximately 75% fewer measurements are required, reducing measurement time. Measurement speed is also improved due to the response time of the DMD pattern generator, which is less than 20μs. An experimental CS-LBIC setup is presented as alongside measurement simulations using a 2D PV device model to explore the capabilities and limitations of the method.

Abstract

Light Beam Induced Current (LBIC) measurements are a useful tool in photovoltaic (PV) device characterisation for accessing the local electrical properties of PV devices. The main disadvantage of a typical LBIC system is measurement time, as a raster scan of a typical silicon solar cell can last several hours. The focus of this paper is the reduction of LBIC measurement time by means of compressed sensing (CS). The CS-LBIC system described in this paper can theoretically reduce measurement time to less than 25% of that required for a standard LBIC raster scan. Measurement simulations of a CS-LBIC system are presented as well as a practical demonstration using a digital micro-mirror array, which further reduces the measurement time by an order of magnitude.

Instead of a raster scan, the PV device under measurement is sampled by a series of patterns and the current map is reconstructed using an optimization algorithm. Simulations of CS-LBIC measurements using the 2D spatially-resolved PV-Oriented Nodal Analysis (PVONA) model developed at CREST are used as a tool to explore the capabilities and verify the accuracy of this measurement technique as well as its ability to detect specific defects, such as cracks and shunts. Simulation results confirm that the CS sampling theory can be applied as an effective method for significantly reducing measurement time of current mapping of PV devices.

An initial CS-LBIC system prototype has been built at the National Physical Laboratory (NPL) and measurements of small area devices (1cm x 0.8cm) using this system are given. The current maps are created using a Digital Micromirror Device (DMD) kit as a pattern generator. The response time of the micro mirror array is less than 20μs. This is another factor in the reduction of measurement time, as the movement time of an x-y translation stage is considerably slower. Initial measurement results show that current maps of PV cells can be acquired with 75% fewer measurements which, combined with the fast response of the pattern generator, can reduce LBIC measurement time by an order of magnitude.

Explanatory pages:

1. Introduction

Light/Laser Beam Induced Current (LBIC) imaging is a non-destructive characterization technique which can be used for mapping the current response of PV cells and modules [1]. For the implementation of these measurements, a raster scan of the sample has to be performed, usually utilising a collimated laser source. High resolution measurements are time-consuming, as they can last several hours for a typical PV cell. In this work a faster approach is presented using the recently developed compressed sensing (CS) theory [2,3]. By applying the CS methodology to LBIC measurements, measurement time can be theoretically reduced to less than 25% of what is currently required. CS-LBIC measurements will combine the CS sampling theory with an LBIC system. Instead of applying a raster scan, a series of patterns or test functions are projected on the sample, utilizing a Digital Micromirror Device (DMD) [4], acquiring M<<N measurements. As the acquired measurements are M and the final required image has N>>M pixels, the problem is underdetermined and the final reconstruction of the image is achieved by means of an optimisation algorithm.

The first prototype CS PV device characterization experimental setup has been built at the National Physics Laboratory (NPL). Initial measurements have proved the feasibility of the method, as current maps have been produced with just 25% of the measurements an LBIC system would need. A theoretical proof of concept has also been performed. A series of simulations have been implemented using the 2D spatially-resolved modelling and simulation tool for PV cells developed in CREST, the PV Oriented Nodal Analysis (PVONA) model [5].

2. Methodology: Compressed sensing

CS is a new type of sampling theory that suggests that sparse signals and images can be reconstructed from incomplete or inaccurate measurements. Consequently, using compressed imaging, an N pixel image can be reconstructed from M<<N observations. For example, in JPEG image compression, most of the information is thrown away at the transformed compression stage (K elements are kept), while the image is reconstructed using only these K elements. The aim of a CS imaging setup is to directly measure only the K necessary coefficients for an almost exact image reconstruction, having applied M<<N measurements for capturing an N pixel image, where K<M.

A compressed representation of a signal, x, is acquired using M<<N linear measurements between x and a set of test functions$\{\varphi_m\}_{m=1}^{M}$, forming $y[m] = \langle x, \varphi_m \rangle$ which is the actual measurement. Stacking test functions $\{\varphi_m\}_{m=1}^{M}$ as rows in a MxN matrix $\Phi = [\varphi_1, \varphi_2, \varphi_3, \dots \varphi_m]$ the problem can be written as [6]:

$$y = \Phi x \tag{1}$$

In general there is loss of information as a result from the transform from x to y, as y has significantly fewer elements than x. Since M << N, there are infinitely many translations, $\{x : y = \Phi x\}$. This is an underdetermined problem with infinite solutions. However, a measurement matrix, Φ, can be designed such that an almost exact approximation of signal x can be recovered from measurement y, if x is sparse or compressible. In practice, few real-world signals are truly sparse, although almost all of them are compressible, meaning that they can be well-approximated by a sparse signal, or are sparse after a transform [7], which means their representation with a basis Ψ is sparse.

The signal reconstruction algorithm must take the M measurements in the vector y, the random measurement matrix Φ and the basis Ψ (transform); and reconstruct the N-length signal x or, equivalently, its sparse coefficient vector α, as $x = \Psi\alpha$ and $y = \Phi x = \Phi\Psi\alpha$. To recover the image x from the random measurements y, the method of least squares (minimizing the ℓ_2 norm) fails with high probability. Instead, it has been shown that using ℓ_1 optimization we can exactly reconstruct K-sparse vectors (K<M<N) and closely approximate compressible vectors stably with high probability. In other words the solution to the underdetermined problem is the x vector (or more precisely the α vector) with the minimum ℓ_1 norm [9]:

$$\hat{x} = argmin\|x\|_1 \text{ subject to } \Phi x = y \tag{2}$$

This is a convex optimization problem that conveniently reduces to a linear program known as basis pursuit [2,10].

3. Experimental setup in NPL

An initial prototype has been built in NPL, in order to test the feasibility of CS characterization of PV devices. The light source is a pigtailed 40mW 658nm laser. The beam is expanded and collimated before the DMD generates the series of patterns to be projected on the sample under measurement. The DMD array has a 1024x768 resolution, with each micromirror having a side size of 10μm. Thus the DMD area is approximately 1cm by 0.8cm. A spatial filter is used for a cleaner image and a camera for beam monitoring. The projection area is the same size as the DMD, a 64x48 image is acquired, which means resolution is approximately 156μm, although higher resolution can also be achieved. A schematic diagram of the setup is presented in figure 1.

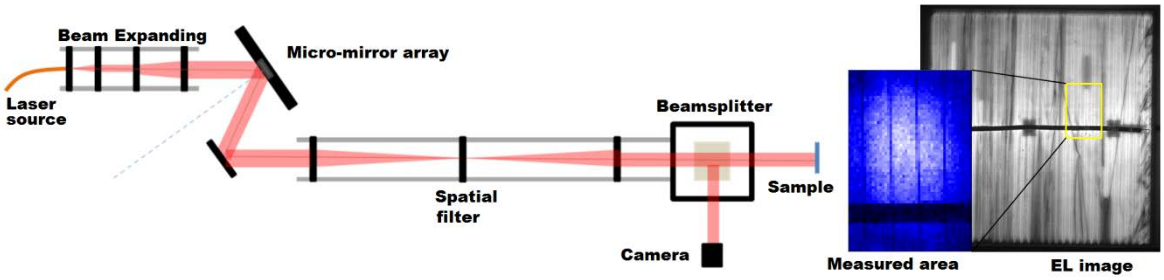

Figure 1: On the left, schematic diagram of the CS LBIC prototype in NPL. On the right, CS-LBIC measurement of a small area and EL image of a mc-Si cell.

Initial measurements show that by acquiring only 25% of measurements compared to a raster scan an almost exact approximation of the current map can be acquired. The response time of the micro-mirrors is less than 20μs, much faster than a point to point move of an x-y stage, thus the measurement time can be further reduced. The DMD generates the random binary patterns that populate the sensing matrix Φ, current measurements of every projected pattern populate the vector **y** and the current map is acquired with the procedure described in the previous paragraph.

4. PVONA Simulations

Parallel to the experimental work, the method is investigated by simulations of CS-LBIC measurements, using the fast PVONA modelling and simulation tool developed at CREST. The PVONA model is used to simulate the behaviour of a cell under illumination with the random binary patterns generated by the sensing matrix Φ. The model generates the measurement matrix y, from which the cell current map is reconstructed. In this way a simulation of compressed measurements can be realised, where specific defects such as cracks and broken fingers can be introduced into the PVONA model, so that the capabilities and limitations of CS LBIC measurements can be investigated. In figure 2 the compressed sensing measurements procedure is illustrated, based on the aforementioned analysis.

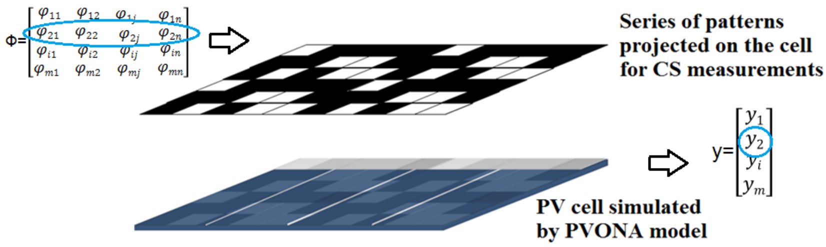

Figure 2: Compressed sensing measurement procedure for a simulated PV device.

Random binary matrices are used to produce the sensing matrix, while the discrete cosine transform is applied (basis Ψ) to provide the sparse representation of the image. For the reconstruction the ℓ1 magic toolkit in MatLab is used [11]. 60 by 60 pixel LBIC maps are produced by the PVONA model, in order to make comparisons with simulated CS-LBIC measurements. Simulation results show that measurement time depends on required resolution and sharpness of the sample details. In figure 3, CS-LBIC simulations are presented with increasing number of measurements from 360 (10%) to 1800 (50%).

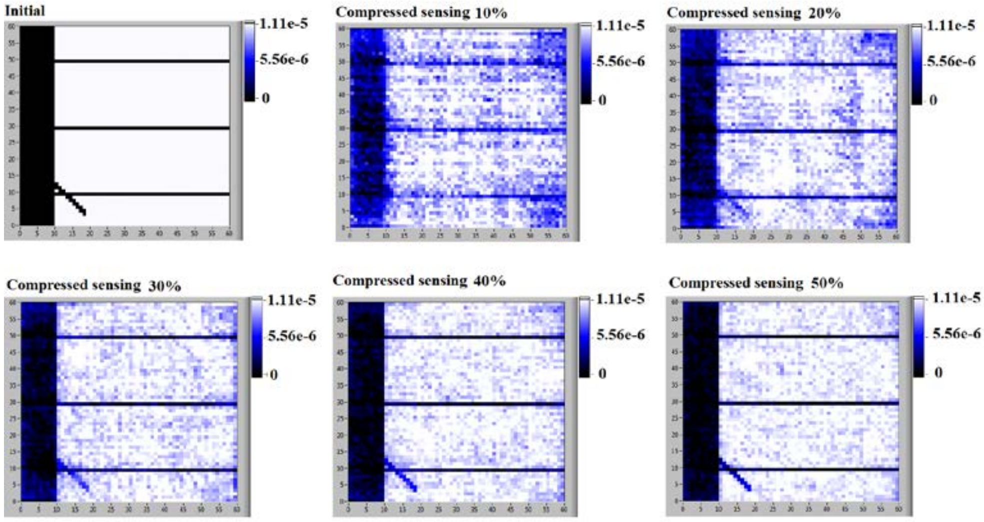

Figure 3: A simulated LBIC map of a 60x60 silicon PV cell with a crack introduced, a busbar and 3 fingers visible and the CS-LBIC simulation results with increasing measurement numbers.

5. Summary

An alternative method for current mapping of PV devices is presented in this paper. The method is based on the compressed sensing sampling theory and can significantly reduce the measurement time of LBIC measurements for PV device characterization. Simulation results using the PVONA model confirm the method's functionality and initial experimental results with a prototype setup illustrate the feasibility of this method.

6. References

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