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Optical technique for photovoltaic spatial current response measurements using compressive sensing and random binary projections

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Abstract. Compressive sensing has been widely used in image compression and signal recovery techniques in recent years; however, it has received limited attention in the field of optical measurement. This paper describes the use of compressive sensing for measurements of photovoltaic (PV) solar cells, using fully random sensing matrices, rather than mapping an orthogonal basis set directly. Existing compressive sensing systems optically image the surface of the object under test, this contrasts with the method described, where illumination patterns defined by precalculated sensing matrices, probe PV devices. We discuss the use of spatially modulated light fields to probe a PV sample to produce a photocurrent map of the optical response. This allows for faster measurements than would be possible using traditional translational laser beam induced current techniques. Results produced to a 90% correlation to raster scanned measurements, which can be achieved with under 25% of the conventionally required number of data points. In addition, both crack and spot type defects are detected at resolutions comparable to electroluminescence techniques, with 50% of the number of measurements required for a conventional scan. [DOI: 10.1117/1.JPE.6.025508]

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1 Introduction

With renewable energy on the rise globally, the market for solar photovoltaic (PV) products is expanding rapidly. As a consequence, there is a need for advancement in the technology used to test and verify the physical properties of the PV cells produced.[1] One of the most common methods for measuring the spatial response of a cell is laser beam induced current (LBIC) scanning,[2] where a laser spot is moved across the surface of a test PV cell and the output current is recorded. This technique, while accurate, is also slow as a pixel-by-pixel scan has to be realized, while often many data samples are needed to be acquired for each point to overcome noise. Recent work has proposed the use of a digital micromirror device (DMD) to implement the scan in order to speed up measurements.[3,4] However, the measurement technique still requires a large quantity of data, and thus time.

It has previously been demonstrated[5] that it is possible to recover the response map of a PV solar cell using fewer measurements than those required using a raster technique such as LBIC. This is achieved using compressive sensing algorithms[6,7] from signal processing theory and the projection of binary illumination patterns based on the Hadamard matrix function. A limiting factor in the number of measurements required to reconstruct a PV current map is the sparsity of

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the representation of that signal when described using a standard identity matrix or using the Hadamard series as a basis set. The core of compressive sensing recovery techniques relies on the sparsity of the reconstructed signal and is more effectively implemented in systems that can be described as possessing a high degree of sparsity.

The use of a projection matrix such as the Hadamard series when describing the signal in the Identity dictionary can show a high degree of structure in the full set of measured responses. Certain projections will be more significant, i.e., giving significantly larger or smaller mean signal amplitudes; therefore, it is important that these significant coefficients are included in the measurement process. Unfortunately without *a priori* knowledge of the part under test, there is no way of knowing in advance which rows of the Hadamard matrix are significant. Using an approach based on randomly sampling, these rows lead to the possibility of a highly incomplete measurement series, omitting the most significant measurements.

It is therefore desirable to separate the concepts of the projection matrix from the dictionary, or basis, used to describe the signal. We have found that using a random binary projection matrix gives a high degree of flexibility in the basis sets used for the signal description. This allows for the response map to be reconstructed in a basis set in which it is significantly more sparse than would be when described using the identity matrix as defined by the Kronecker delta. It is demonstrated that significantly fewer measurements are required for reconstructing the PV current response map than in the case of using a Hadamard-based projections.

2 Theoretical Background

One of the most important factors in compressed sensing is the concept of "sparsity" of a signal, which is the number of values needed to describe the signal. Consider a signal x, of length N, which can be described as

$$x = \sum_{i=1}^{N} \psi_i c_i = \psi c,$$

where c_i is a N length column vector of coefficients and ψ is a $N \times N$ orthonormal matrix that forms the basis set of the signal description. This basis set is referred to as the dictionary in which the signal is defined. A signal is called K-sparse if there are $N > K$ values of c_i, which are zero, and thus the signal can be described by only K coefficients. Compressive sensing theory is rooted in the notion that for a known signal x there exists a dictionary in which a sparse representation is possible. K is required to be as small as possible to minimize the number of measurements necessary to reconstruct the signal.

If the behavior of signal x was known, it would be easy to determine the optimal dictionary. However, the aim is to measure this signal, i.e., derive this knowledge. This is ultimately the limitation of using the basis set as the projection matrix, which is the case when using Hadamard patterns, and requires a way of incorporating nonbinary dictionaries to be developed. The sampling of signal x can be considered using an $M \times N$ projection matrix ϕ, which generates a series of voltages y, i.e., $y = \phi x$. This can be rewritten as $y = \phi\psi c$ and we can now describe the PV as a simple linear equation $y = \theta c$, in terms of a measurement matrix $\theta = \phi\psi$, and a series of sparse coefficients c. By probing the PV sample with binary sampling patterns ϕ, the original signal x can be determined by performing compressed sensing in the transformed domain of the dictionary ψ. The matrix θ is an $M \times N$ matrix, which allows all rows of the dictionary to be addressed by an incomplete series of measurements and thus avoids the dilemma produced using Hadamard mapping, where exclusion of important measurements may occur through lack of prior knowledge.

The only constraints in the choice of conditions for this are that the rows of our projection matrix cannot sparsely represent the columns of the dictionary, known as the incoherence condition, and that for any 3K-Sparse vector v:

$$1 - \epsilon \le \frac{\|\theta v\|_2}{\|v\|_2} \le 1 + \epsilon$$

for $\epsilon > 0$, known as the restricted isometry property.[8] It happens that these properties can both be met through forcing the measurement matrix ϕ to contain random entries.[9]

Previous results from using Hadamard dictionaries to reconstruct the signal[5] showed that the reconstruction using an l_1-norm minimization technique[10] did not produce an optimal reconstruction. However, this was determined to be a consequence of the nonsparse descriptions of the spatial response profile in the Hadamard domain. As significantly sparser descriptions are considered, the l_1-norm minimization technique is revisited in more detail.

The reason that it is nontrivial to solve an underspecified series of linear equations is that for every vector of coefficients s with a valid solution to $y = \theta s$, there are infinitely many other solutions of the form $s' = s + r$ where r is any vector in the kernel of the reconstruction matrix θ. By definition, the null space of the matrix θ will always contain the zero vector, $\bar{0}$, ensuring that the combination vector subspace of all $s + r$ will contain the desired sparse coefficient vector. This compound vector s' is therefore a translation of the desired sparse coefficient vector in the space $\mathbb{R}^N$.

To understand why l_1-norm minimization is ideal for sparse signal reconstruction, the fundamental geometry has to be considered. The "traditional" magnitude of a vector is the square root of the sum of the squares of each vector coefficient, i.e.,

$$\|X\| = \sqrt{X_1^2 + X_2^2 + \cdots ..X_N^2}.$$

This is the more generally known as l_2-norm of the vector X. In general, we can express the l_p-norm as

$$l_p\text{norm} = \|x\|_p = (|x_1|^p + |x_2|^p + \cdots .|x_N|^p)^{\frac{1}{p}}.$$

For the sake of convenience let us look at the unit circle of various l_p-norms in the real space $\mathbb{R}^2$ is considered, in which also lies the translated sparse vector s'. The distribution in space of all values of the unit l_2-norm is spread homogeneously in a circle around the origin. For the l_1-norm, however, the distribution extends further out along co-ordinate axes. This demonstrates why the l_1-norm minimization technique is used rather than the l_2-norm, as the intersection of the l_1-norm with the vector subspace s' will occur in a region close to a co-ordinate axis with a higher probability, and of course a vector that lies along co-ordinate axes is by definition sparse.

Separating the sensing matrix from the dictionary now allows for more freedom in the choice of how to reconstruct the measured signal. As mentioned earlier, the description of the current response map of the PV sample was not sparse when described in either the identity or Hadamard basis sets, and as such reconstruction algorithms designed for recovery of sparse signals will not provide optimal results. The use of discrete cosine transforms and discrete sine transforms (DCT and DST) as dictionaries is investigated instead as the dictionaries, as they are expected to provide much sparser descriptions of our desired signal.

3 Experimental Details

A collimated pigtailed diode laser beam of wavelength 632.6 nm was projected onto the surface of a TI 0.7" XGA DMD, which was used to display the series of random test patterns required for compressive sensing as seen in Fig. 1. The plane of the test patterns was conjugated onto the surface of a dye-sensitized PV sample, chosen for the irregular shape of the photoreceptive area. This was done in order to explore the ability of the compressed sensing technique to quickly recognize a faulty sample. The size of the illuminated area was $\sim$10 mm $\times$ 14 mm, which corresponded to $\sim$0.05 suns irradiance. The output signal from the PV was fed into a Vinculum SP042 current-to-voltage amplifier before being measured via an NI USB 6211 analog-to-digital converter. The voltage signal was sampled at 1 KHz and averaging techniques were used in order to compensate for the short period variability in illumination source. The algorithm used to reconstruct the current map from the series of measured signals was the $l_{1\text{dantzig}}$ operator from the widely used l_1-magic collection. This is a series of freely available MATLAB® routines for solving compressive sensing problems. By inputting the series of measured signals from the PV and corresponding measurement matrix, the $l_{1\text{dantzig}}$ operator returns the output of the inverse transform of the current response map. By applying the initial transform used to create the measurement matrix θ, as discussed in Sec. 2, a reconstructed current map is produced.

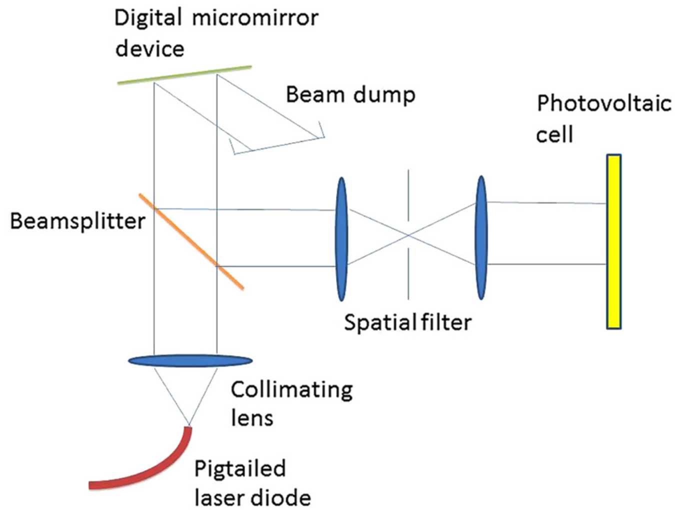

Fig. 1 Experimental design of the compressed sensing system. DMD is addressed with a planar beam on a tilt to ensure retroreflection into the lens relay system. The PV cell is placed conjugate to the DMD surface.

4 Results and Discussion

A series of random IID binary matrices are projected onto the surface of the PV element, with each matrix forming successive rows of the overall sensing matrix. By performing an l_1-norm minimization on the discrete cosine transform of the sensing matrix and the corresponding one-dimensional vector of photocurrent responses, a significant reduction is observed in the number of measurements required for the structural features of the sample to become visible. As presented in Fig. 2, the use of a discrete cosine dictionary allows for this reconstruction in approximately a fifth of the data points needed for a raster scan (150 out of 768), with a 90% correlation to the standard LBIC raster scanning technique implemented using the mirror array. This can be increased to 95% when using 350 measurements. This shows a vast improvement over the use of Hadamard projection matrices where over half of the measurements are required to see comparable result accuracy. For high M a drop in the correlation coefficient is observed, which can be attributed to the difference in noise composition between the compressive sensing measurements and the raster scan measurements.

Figure 3 shows the growth of the linear correlation of the recovered response maps as a function of increasing number of measurements. Unlike the behavior seen in Ref. 5, where there are sudden jumps, here we observe a rapid increase in the reconstruction accuracy up to approximately one-fifth of the total data points. The correlation then increases slowly, plateauing at a value of ~95%. The sudden drop in accuracy when approaching the number of measurements required for LBIC is considered to be a combination of noise contributions as well as effects arising from the fact that the support of each row of the sensing matrix is not equal. This then results in some areas on the PV being sampled more often than others. This consistent reconstruction success is a direct result of separation of sensing matrix from the dictionary. By addressing the whole dictionary identity matrix with the incomplete sensing matrix ensures that there is no omission of terms corresponding to vital spatial frequencies present in the behavior of the PV under test.

In order to investigate the stability and potential of this technique at higher resolutions, we simulated the compressive photocurrent mapping of PV samples with various morphologies at a resolution of 101×101 pixels, equivalent to 98 μm. These included a perfect fault free PV, one with a crack in and one with both a crack and a spot type defect. The behavior of the correlation to raster scanned measurements of this can be seen in Fig. 4 for both cosine and sine transforms. Instead of plateauing after the first 10% to 20% of measurements, here we can observe that there is a continual trend for increase in the reconstruction success up to a value of 1 at 100%. The stability of the compressive photocurrent mapping technique was verified through multiple simulations of each parameter set ~50 times and then bootstrapping the calculated values to assess

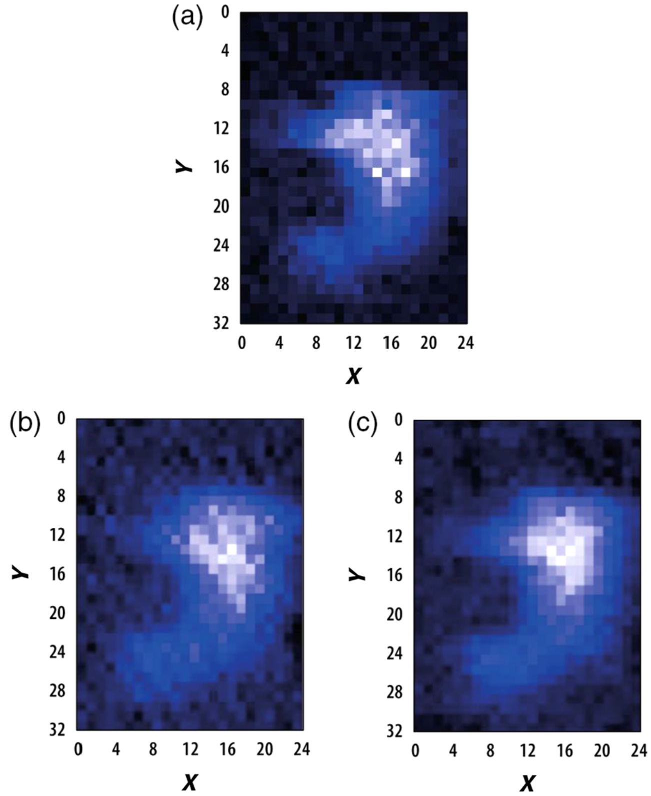

Fig. 2 (a) Response map of a dye-sensitized PV sample when raster scanned (768 measurements). The response maps when obtained through using l_1-norm minimization techniques of (b) 190 and (c) 350 measurements using a discrete cosine dictionary.

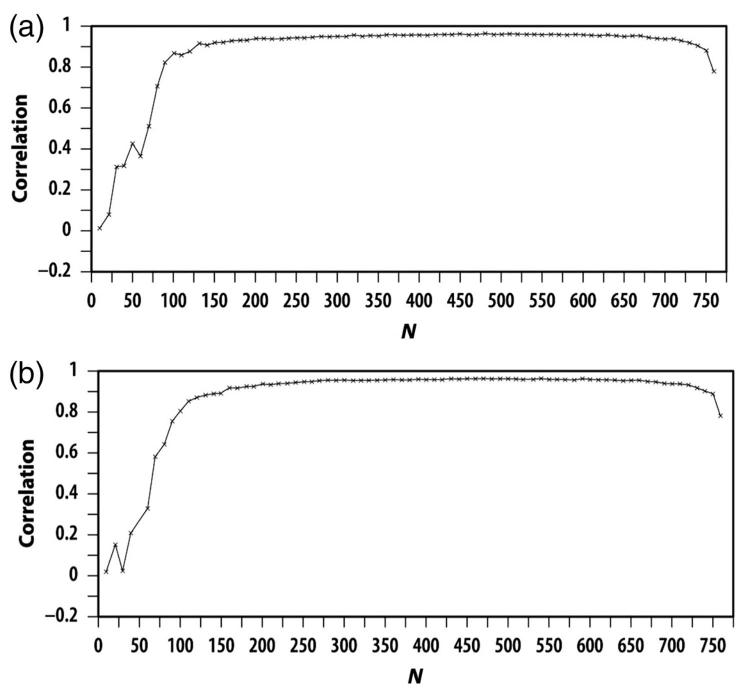

Fig. 3 Plots of the evolution of the correlation between raster scanned map and that obtained through compressive sensing for the cases of (a) discrete sine dictionary and (b) discrete cosine dictionary. In both cases, a very rapid rise in reconstruction success is observed, which plateaus at roughly half of the measurements required for raster techniques.

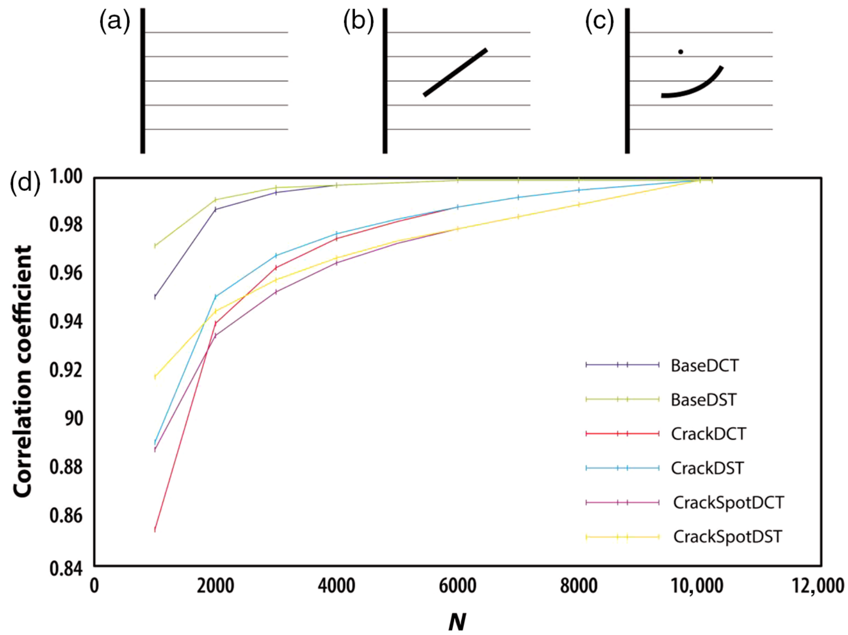

Fig. 4 Simulated growth of the correlation coefficient comparing the maps produced through compressed sensing methods with a perfect sample. Here we see the trends for three different samples (TOP): (a) without defect, (b) with a crack type defect, and (c) with a crack and a spot type defect. Different expected fault morphologies are observed to greatly influence the reconstruction success. (d) The behavior of the growth in correlation to raster scanned results as a function of increasing number of measurements.

repeatability. We found that the bootstrapped mean correlations fell within one standard deviation of the original values. We can also observe that the morphology of the fault in the PV can greatly influence the success of the reconstruction process. The DST is seen to be more successful at this recovery at low numbers of measurements for all three defect scenarios, and this increased suitability over the DCT is likely a consequence of the initial boundary conditions placed on the reconstruction algorithm by the overall shape and symmetry properties of the sample.

Figure 5 presents a further experimental development of the compressive sensing technique along with a comparison against results obtained through electroluminescence measurements. A monocrystalline silicon (mc-Si) solar cell was placed under random binary projections at 768 nm at a much higher resolution than the previous results in this paper, reconstructing a

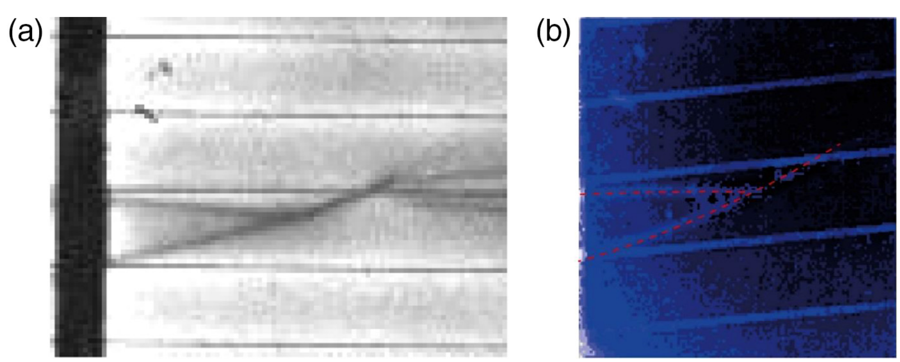

Fig. 5 Comparison between (a) electroluminescence imaging of an area of an mc-Si PV sample against (b) a current map of the same area of the sample produced by compressive sensing measurements. This full scan of this area would cover over 16,000 measurements, and using half of this we can detect both spot type defects and a significant crack, indicated with the red dotted line on right. Image on right obtained using a resolution of 80 μm.

128×128 pixel current map, with effective pixel size of $\sim 80\ \mu m$. It is clear that spot type defects are detectable in the top left of the recovered area, both on and between the fingers. Significantly, it is also possible to detect cracks in the PV sample, circled in red. Both of these artifacts are observed using half of the number of measurements that would be required for a full raster scan of the sample. This provides exceptionally strong support for the claim that the use of compressive sensing can offer a significant speed increase over typical LBIC methods for the current mapping of PV devices. To achieve a reconstruction as seen in Fig. 5 requires ~ 8 min of data acquisition time, and similar additional processing time, which would require several hours when using standard LBIC techniques.[11] In addition, due to approximately half the sample being illuminated at any one time, there is a significantly increased signal-to-noise ratio when compared with single point, raster scanned measurements. Furthermore as this technique directly probes the current response of the PV test element, it is capable of picking up a much wider range of potential fault types than any standard optical imaging technique. The use of compressed sensing to perform diagnostics of PV elements as seen above offers also offers a vastly cheaper alternative to EL techniques. EL systems require a high cost, high-resolution IR camera for measurement acquisition, whereas with the compressed sensing technique the PV itself is acting as the detector.

One of the most flexible aspects of the system described here is that by using a DMD it is possible to adjust the resolution of the sensing matrices used, which results in the ability to control the resolution of the images obtained. In the reconstruction seen in Fig. 5, we are using blocks of 6 actuators per pixel (actuator size $\sim 13\ \mu m$); however, this can be varied as the demands of the measurement situation requires and this directly affects the speed of data acquisition and reproduction. The results presented here do not represent the theoretical maximum speed of this technique. The DMD used in this work is capable of display speeds of over 30 KHz and optimizing the current measurement procedure; it is expected that it would be possible to acquire measurements over a timescale of seconds, with a resolution of under 50 μm, i.e., working at the speed at which the solar cell can respond without being affected by cell capacitance. To achieve higher speed lower resolution sampling matrices could be used, resulting in fewer measurements, which could be processed faster, enabling this technique to measure multiple test pieces in under a second. The high speed and low cost of the system allows the potential for implementation to a production line environment. Furthermore by eliminating the mechanical translation components required for LBIC techniques, as well as inherently needing significantly fewer measurements, the ceiling for measurement time using compressive sensing techniques will always be lower.

5 Conclusions

As an expansion of previous work, the sampling technique of compressed sensing is introduced for faster current mapping of PV devices. Rather than scanning the sample using binary functions directly, it has been shown that by randomly sampling the PV and then reconstructing within a transformed domain, a significant increase in the speed of the measurement process is achieved. In addition to achieving a 90% correlation with raster scanned data in initial results, it is also shown that a reconstruction at comparable resolution to electroluminescence results is possible, which contain identifiable cracks and spots. The results described in this work are considered to provide a solid framework in which a fast PV current mapping measurement system can be implemented, significantly reducing measurement time compared to standard LBIC systems.

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