

S. Rao, S. Katoch, A. Spanias, P. Turaga, C. Tepedelenlioglu, R. Ayyanar, H. Braun, J. Lee, U. Shanthamallu, M. Banavar<sup>+</sup>, D. Srinivasan<sup>++</sup> SenSIP Center, School of ECEE, Arizona State University, + ECE, Clarkson University, ++ Poundra LLC

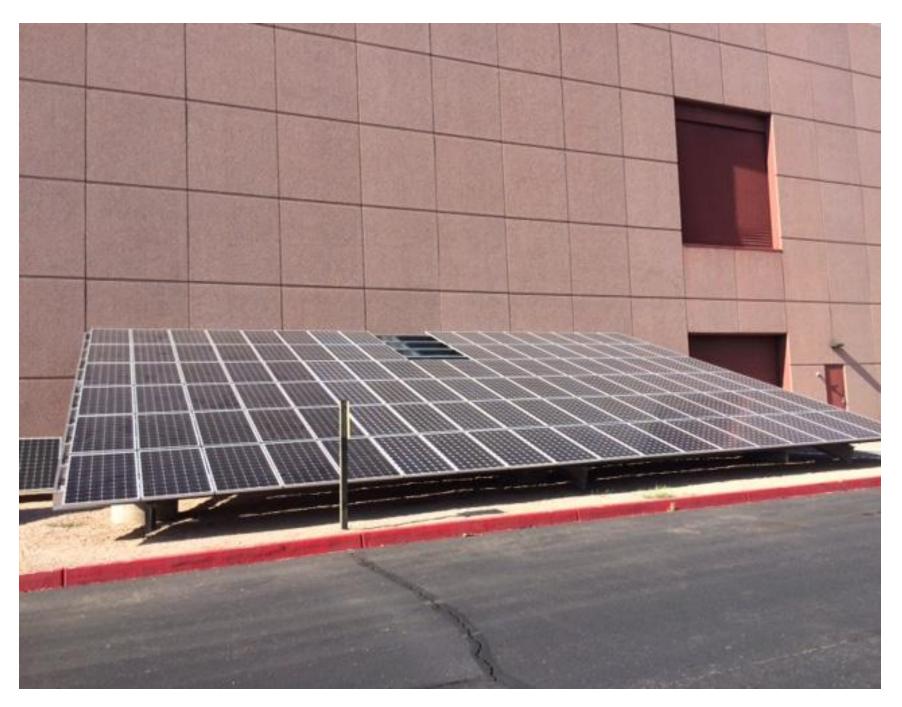
### MOTIVATION

**Open problems in PV array management** 

- **Efficiency improvement in solar energy farms;**
- **G**Faults detection and power output optimization;
- **Find correlation between observed imagery and PV circuit characteristics;**
- Skyline feature prediction for better power grid control;

### **PROJECT AIM**

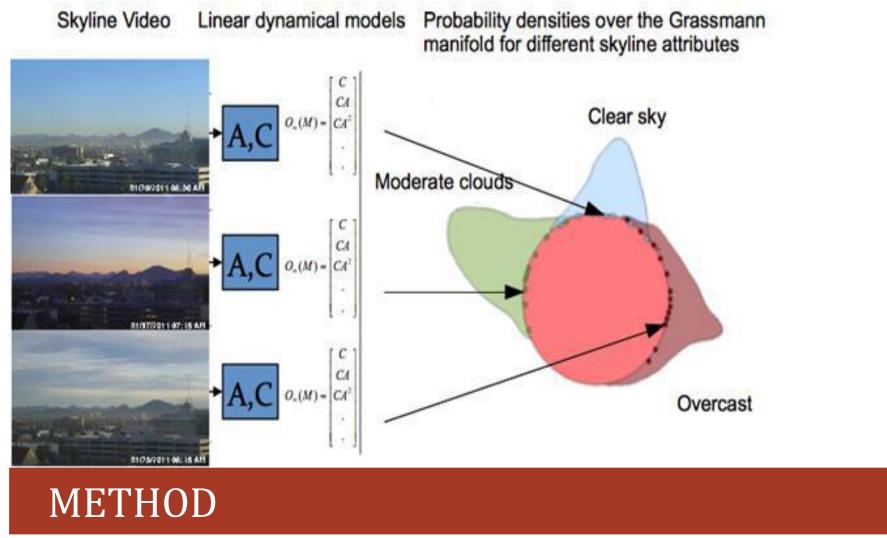
- **Power Output Optimization by skyline feature** prediction using imaging algorithms. [1]
- **Using ML techniques with sensor fusion data from** PV modules for fault detection.[2]

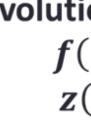


The SenSIP 18kw (104 panel) experimental facility established at ASU with industry collaborators [3].



ter Template Designed by Genigraphics ©2 1.800.790.4001 www.genigraphics.com





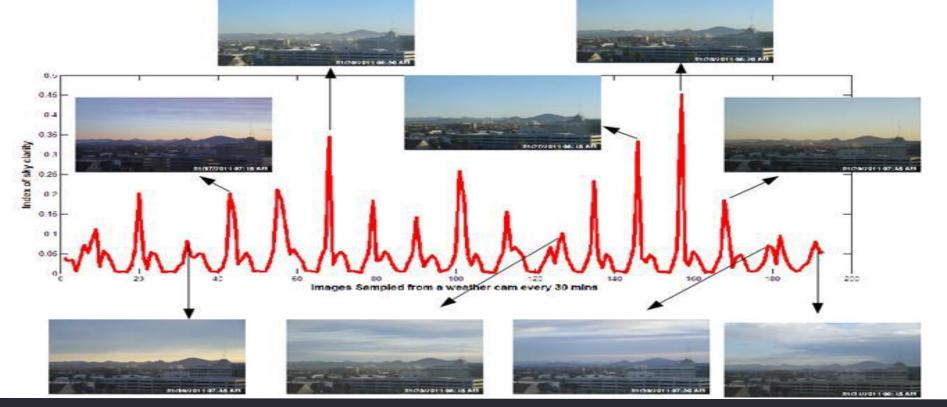
Where  $z \in \mathbb{R}^d$  is the hidden state vector,  $A \in \mathbb{R}^{d * d}$ 

the transition matrix,  $C \in R^{p*d}$  the measurement matrix. [4]

**Parameters of LDS model are best viewed as subspaces** formed by columns of observability matrix.

## PRELIMINARY RESULTS

**A** small training set with a few segments as 'clear', 'moderate cloudy', and 'overcast' was used to learn a probability density function on the Grassmannian.



# **A Cyber-Physical System Approach for Photovoltaic Array Monitoring and Control**

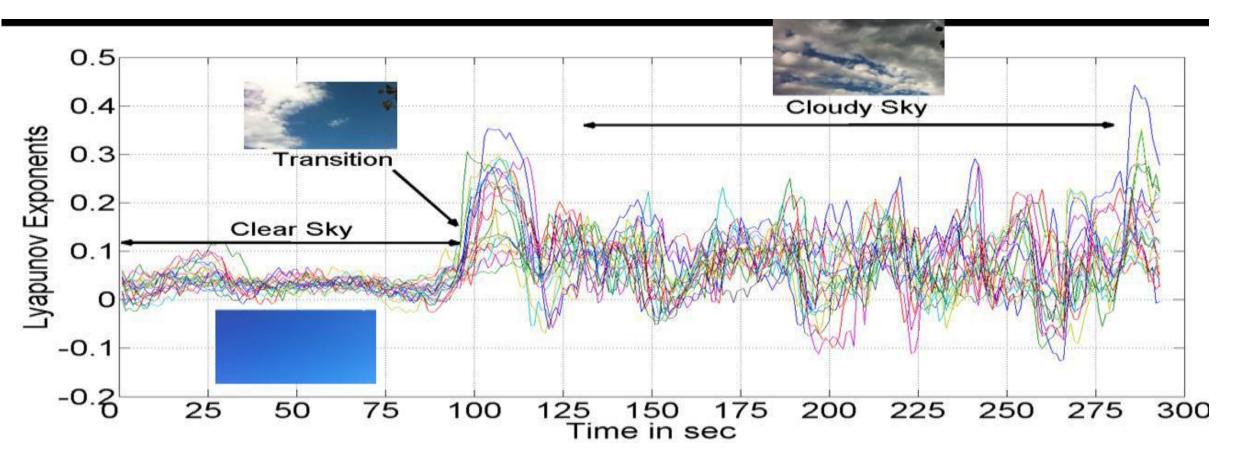
### **PROPOSED ALGORITHM**

**I**f(t) is the sequence of texture and color features extracted from a video of skyline indexed by time.

**Evolution of features is marked by** 

$$(t) = Cz(t) + w(t),$$
  $w(t) \sim N(0, R)$   
 $(t+1) = Az(t) + v(t)$   $v(t) \sim N(0, Q)$ 

Image-based measures of sky-clarity, an attribute useful for predicting shading. This metric was created from dynamical models of image texture, with a manifold-based metric on dynamical model parameters. Sample images at various times show how the index separates 'clear skies' and 'hazy/cloudy skies'.



Spatio-temporal modeling of sky videos using GIST and largest Lyapunov exponents; with time stamps for clear sky, transition from clear-cloudy sky and cloudy sky.

### ONGOING & PLANNED WORK

- horizon viewing cameras.

### REFERENCES

[1]J. Thiagarajan, K. Ramamurthy, P. Turaga, A. Spanias, Image Understanding Using Sparse Representations, Synthesis Lectures on Image, Video, and Multimedia Processing, Morgan & Claypool Publishers, ISBN 978-1627053594, Ed. Al Bovik, April 2014 [2] H. Braun, S. T. Buddha, V. Krishnan, A. Spanias, C. Tepedelenlioglu, T. Takehara, S. Takada, T. Yeider, and M. Banavar, Signal Processing for Solar Array Monitoring, Fault Detection, and Optimization, Synthesis Lect. Power Electronics, J. Hudgins, Ed. Morgan & Claypool, vol. 3, Sep. 2012. [3] A. Spanias, C. Tepedelenlioglu, E. Kyriakides, D. Ramirez, S. Rao, H. Braun, J. Lee, D. Srinivasan, J. Frye, S. Koizumi, Y. Morimoto, "An 18 kW Solar Array Research Facility for Fault Detection Experiments," Proc. 18th MELECON, Tech. Co-sponsor IEEE Region 8, T1.SP1.12, Limassol, April 2016. [4] G. Doretto, A. Chiuso, Y.N. Wu, A. Soatto, "Dynamic Textures," International Journal of Computer *Vision (IJCV),* vol. 51, no. 2, pp. 91-109, 2003.

ACKNOWLEDGEMENTS

This research is supported in part by the SenSIP center and the NSF CPS program #1646542.

Sensor Signal and Information Processing Center https://sensip.asu.edu

Sen

It is possible to develop early warning systems using a small network of

The transitions obtained using Lyapunov exponents can be used for prediction. Long term prediction can be performed by reconstructing the hidden phasespace of the true dynamic system using delay embeddings.

