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

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***Abstract*— In this paper, we describe a Cyber-Physical system approach to Photovoltaic (PV) array control. A machine learning and computer vision framework is proposed for improving the reliability of utility scale PV arrays by leveraging video analysis of local skyline imagery, customized machine learning methods for fault detection, and monitoring devices that sense data and actuate at each individual panel. Our approach promises to improve efficiency in renewable energy systems using cyberenabled sensory analysis and fusion.**

## I. INTRODUCTION

The efficiency of solar energy farms requires detailed analytics and information on each panel regarding voltage, current, temperature and irradiance. We describe machine learning and computer vision approaches for improving the efficiency and reliability of utility scale solar arrays. Efficiency improvements are accomplished through prediction of complex dynamical system parameters using sensors and sensor fusion. The methods presented in this paper will be implemented on state of the art testbed shown in Figure 1. This testbed was developed by the Sensor Signal and Information Processing (SenSIP) Center and involves an 18kW array of 104 panels. Cyber-physical methods that include imaging and machine learning algorithms for shading prediction and fault detection are being developed to improve efficiency. These methods will be validated on the SenSIP Solar facility.

Figure 1. The SenSIP 18kw (104 panel) experimental facility established at ASU with industry collaborators.

Camera and satellite sensing of skyline features as well as parameter sensing at each panel provides information for fault detection and power output optimization through sensor fusion and appropriate actuator programming. Machine learning and fusion enables us to implement robust shading prediction.

## II. PROPOSED SYSTEM

Networked PV Array Concept enabling the weather feature correlations, local shading prediction, decision support, and fault detection.

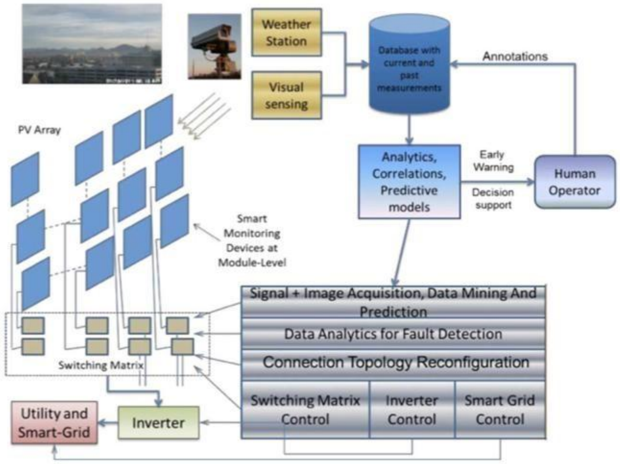


Figure 2. Networked PV Array Concept.

A utility-scale PV array consists of solar panels that are connected in series, forming strings, which are in turn connected in parallel. The DC output of the array is converted to AC using inverters. Shading, weather patterns and temperature can severely affect power output. To minimize these effects, individual panel current-voltage (IV) measurements, weather information , and imaging data are essential. Moreover, controlling the power output is possible through matrix switching (i.e., changing array topology enabled by SMD relays) of PV panels allowing for different interconnection options. We optimize utility scale PV array systems by exploiting the measured I-V, imaging, and weather data. The smart monitoring devices connected to each PV panel collect the individual panel metrics (current, voltage, and temperature) periodically (about every 8 seconds). The cameras provide updates at the rate of 20-30 frames per second. The algorithmic and image/data analysis unit are equipped with various state of the art algorithms for imaging, data mining and prediction that identify and track various important timevarying events and patterns. The algorithms operate on PV array measurements and on parametric models to detect and remedy faults using SMD panel switching (Fig. 2) or bypassing if necessary.

## A.FAULT DETECTION USING MACHINE LEARNING IN PV ARRAYS

Several faults occur in PV Arrays. These are caused by shading, soiling, inverter faults and manufacturing mismatches. Data acquired during faults tends to luster in the feature space consisting of current, voltage and temperature measurements.Certain aspects of our algorithmic and experimental research using this facility will focus on modeling faults interns of clusters and using machine learning algorithm to form and track these clusters.
PV arrays are reliable, but any fault which does occur is difficult to detect and repair. Studies of PV faults have shown a mean time to repair (MTTR) of between 3 and 19 days for conventional arrays with data collected only at the inverter. Clearly there is an opportunity to improve fault handling in PV arrays, using statistical signal processing methods, on SMD data and which can lead to automated early detection and precise diagnosis of PV problems.

### i. Machine Learning in fault detection

The use of machine learning in fault diagnosis can be formulated as a multiple hypothesis testing problem. Machine learning is useful for the detection and the identification of the type of the fault. For example, if one of the arrays receives less sunlight due to shading, machine learning could help identify the error in the shading conditions.

A classification algorithm for fault detection must have the following properties. First it must accurately classify the PV array's condition. It must be adaptable to different array configurations without extensive data collection for each individual array. It must be able to recognize each fault class from a very small number of examples.Itshould take advantage of our prior knowledge of the electrical behavior of PV arrays (e.g. equal current within a string), rather than having to learn these relationships through the training data. It should be capable of reacting to the 'unknown unknowns' i.e. faults the system designers did not anticipate.

### ii. Using a simple K-means clustering algorithm

The *k*-means algorithm was chosen as an initial approach to machine learning-based fault detection. K-means clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. Simulated fault data were obtained using the UW-Madison PV module performance module and a SPICE circuit simulation package. K-means algorithm was applied on these data.

The dataset was gathered under normal (well irradiated) conditions of temperature with high levels of current flowing through each panel. To simulate a shaded panel, one of the panels was assigned a lower irradiance value. The data for the same was obtained and trained with the k-means algorithm.

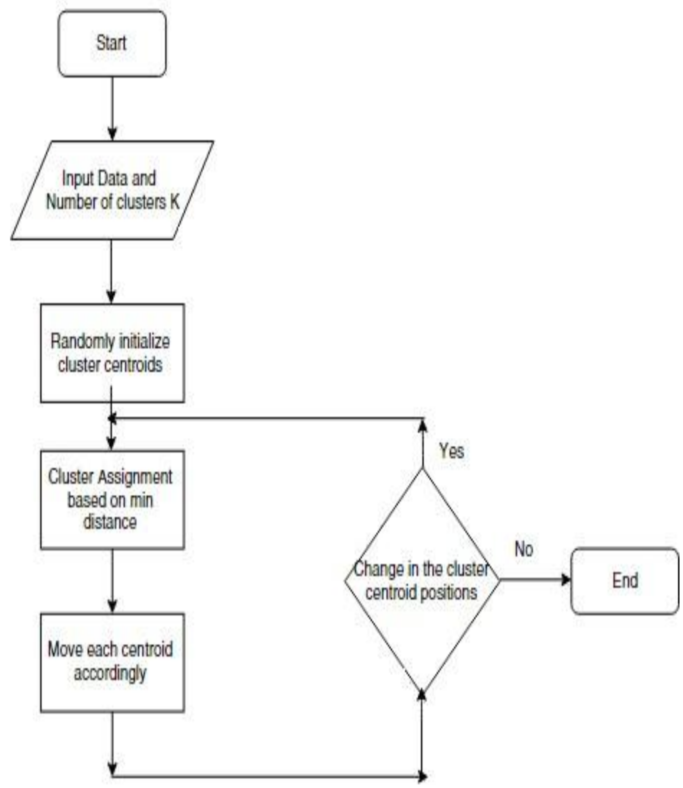


Figure 3: Flowchart demonstrating the operation of the KMeans algorithm.

## B. DYNAMIC MODELS FOR SKYLINE VIDEOS

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**A. Riemannian geometric interpretation of dynamic model parameters**

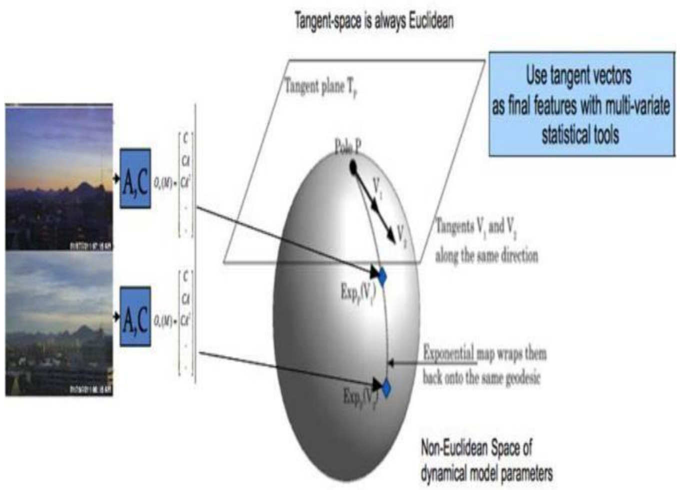


Figure 4: Illustrates exponential and inverse exponential maps.

Since we are interested in performing various statistical correlation analyses with the estimated skyline dynamical models, we need to first consider the challenges in performing a standard multivariate statistical analysis if the underlying state space is non-Euclidean. These analyses require the use of tangent-spaces and exponential/inverse exponential maps. We illustrate the notion of the exponential map in the Figure 3. This figure illustrates exponential and inverse exponential maps. These mappings extend the wealth of multivariate statistical machine learning algorithms to our general manifolds. The tangent vectors represent the final features that will be used in conjunction with other machine learning tools for mapping video features to skyline attributes. These tools allow one to locally linearize the parameterspace, and employ classical multi-variate statistical tools, such as computing probability densities from sample data and regression to relevant attributes.

**B. Temporal prediction of dynamical systems**

Shown in Figure 5, is the general framework for constructing conditional probability density functions over linear dynamical model parameters for skyline attributes such as „clear‟, „light clouds‟, and „overcast‟.

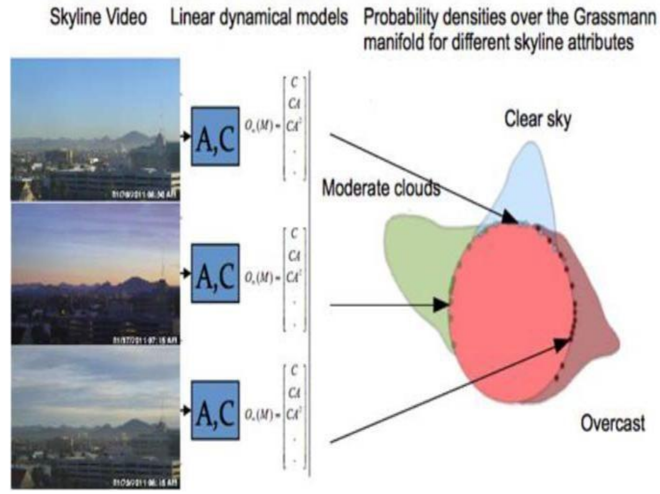


figure 5. illustration of proposed algorithm

Figure 5 shows the illustration of proposed algorithm for estimating conditional densities of skyline features from video measurements. Video streams are modeled as linear dynamical models, whose parameters are considered as points on a Grassmann manifold. Conditional pdfs of sky attributes are estimated using Riemannian geometric tools.

The classification methods of dynamic textures as described previously are effective in short durations of time, when one can assume that the dynamic texture has wide-sense statistical stationarity to further enhance prediction, we need to consider looking forward in time, and anticipating dynamical evolution. Assuming linear dynamics and wide sense stationarity is often an unrealistic assumption when faced with the task of predicting the evolution of a dynamical pattern. For long-term prediction, we consider the problem of studying the evolution using nonlinear tools, which avoids making restrictive assumptions on parametric forms. The basic principle we adopt is one of reconstructing the hidden phasespace of the true dynamic system using delay embeddings. Note here, that the dynamical system under consideration is multi-variate to begin with, since the extracted features are of the order of pixels in the image. From the reconstructed phasespace, the prediction problem is tackled using simple regression models in the phase space. This contrasts with prediction using regression models in the observation space, which is much harder due to the nonsmooth properties of the observation sequence. If the phasespace reconstruction is properly achieved, the evolution in the phase space is much smoother, which will allow prediction of the next few phases. Mapping from predicted phases to expected pixel measurements can be achieved, which will allow us to use the previously developed linear models for classification into one of several shading categories.

## III. Results And Discussions

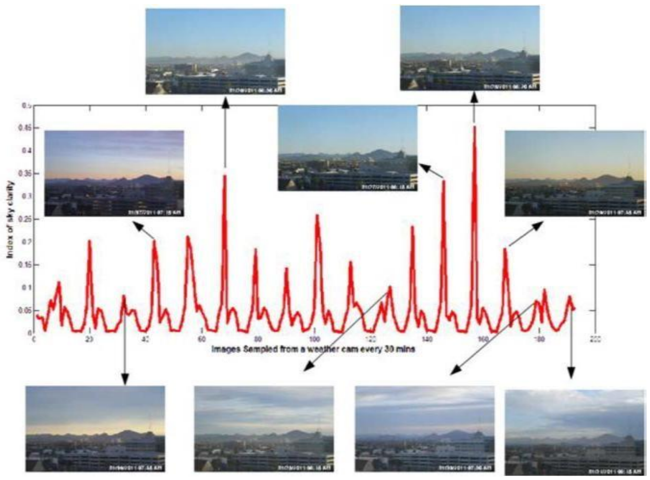

Figure 6. Image-based measures of sky-clarity

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". Using a small network of horizonviewing cameras it is possible to develop early warning systems.

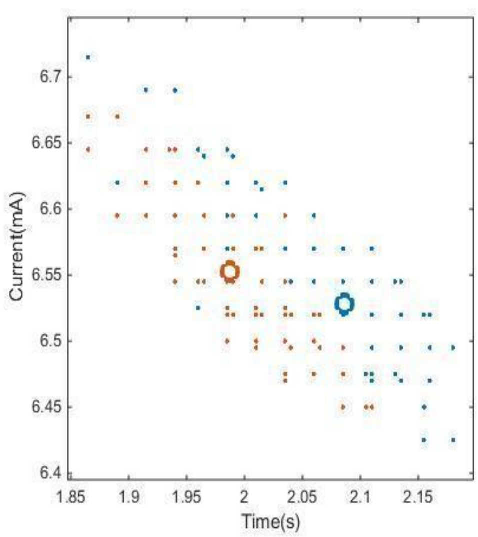


figure 7: separation between normally operating and faulty panels.

Preliminary results indicate feature level separation between the data obtained from a faulty panel and data as obtained from a normal (working optimally) panel. This in the future could help in identifying the type of fault associated with each PV panel.

The results obtained at a preliminary stage are shown in Figure 7. Each data point in the feature space represents the measure of current by the PV panel. The faulty and non-faulty panels can be separated by means of a linear classifier. Thecentroids in the preliminary simulation shown in Figure 7 separate out well and tend to separate faulty and normal conditions.

## IV. CONCLUSION AND FUTURE WORK

We addressed the problem of PV array monitoring and control using advanced imaging and machine learning algorithms. We proposed integration of machine learning, image processing and optimization techniques for real time monitoring of PV arrays. Preliminary results for fault detection demonstrated clustering successfully faults and our simulations with imaging prediction promise significant efficiency improvements.

The fault detection algorithm presented here promises the ability to detect the wide range of conditions affecting array output. The algorithm may be deployed as part of a compre- hensive monitoring system that improves array efficiency and availability with a minimum of human operator involvement. Although the algorithm shows good performance in simulations,several opportunities for improvement exist.first, the sampling period of the monitoring system may be increased so that voltages and currents may be treated as quasi-stationary. The algorithm may then be altered to consider data over a short time window rather than a single snapshot. Another approach is to incorporate measurements of irradiance and/or module temperature in predicting array output.

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