

# UCLA

## Posters

### Title

Imagers as Biological Sensors

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# Imagers as Biological Sensors

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## Introduction: Use imagers to capture hard-to-measure natural phenomena

### Some phenomena are difficult to measure

- Existing sensors are cannot be used in the field  
Measuring some biological phenomena, like CO<sub>2</sub> uptake, requires *destructive* or *invasive* instrumentation. Such modification of the environment make any resulting measurement unrepresentative of the phenomena.
- The phenomena occurs over a large spatial-temporal area  
Automated approaches towards detecting the presence of species can dramatically improve the scope in which an ecologist can investigate ecological change.

### Use imagers to measure phenomena

- Construct a procedure using imagers as sensors  
Use state-of-the-art computer vision, image processing, and statistical learning algorithms to model the target signal using *domain relevant features*. Potentially acquire training data from representative *laboratory experiments*.
- Collapse hours of video into summary statistics  
Use *intrinsic properties* of a particular process instantiation to remove redundancy. These properties will take the form of visual cues or other, more easily deployed, traditional sensors.

## Problem Description: Varying field conditions and limited ground truth present challenges

### Estimating CO<sub>2</sub> flux

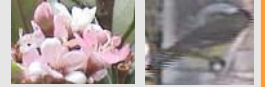


#### Challenges

- Field lighting conditions are variable
- Not all features are meaningful
- Estimates must be validated

**Approach:** Extract color based features and infer from a regression based model of CO<sub>2</sub> data collected in a laboratory.

### Detecting/cataloging animals



#### Challenges

- Large background nuisances
- Mimicry
- Low resolution objects of interest
- Unknown categories

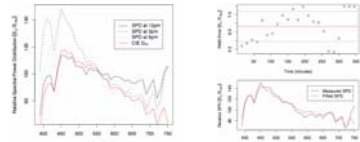
**Approach:** Enforce spatial-temporal consistency and Categorize "interesting" objects based on multi-view features

## Proposed Solution: Construct an application evaluated procedure

### Moss CO<sub>2</sub> flux

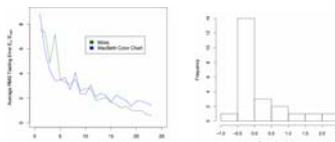
- Goal:** Ecologists want to determine the effect of short summer rain events on the moss' ability to survive
- Obstacles:**
  - There are no available sensors
  - Methods suggested by previously ecological studies have insufficient temporal resolution

### Incident Lighting Modeling



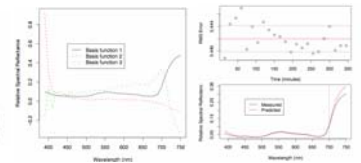
- Measured illumination (left) is similar to D<sub>65</sub> although it is slightly bluer
- Model (by Judd et. al.) fits well (right top), with a slight temporal component to the error
- Even the sample with largest error has *minimal error and correct characteristic shape* (right bottom)

### Lighting Estimation

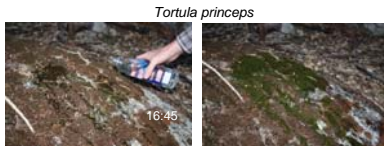


- Uses the Color by Correlation algorithm; accuracy is good with enough training examples (left) With 12 training examples, we find that *error clusters near zero* (right)
- Interestingly, performance was comparable with and without JPEG compression

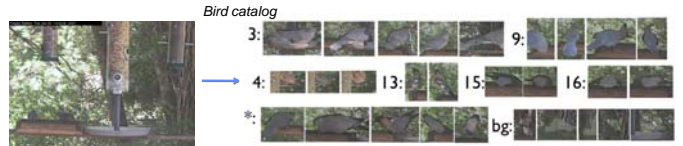
### Reflectance Estimation



- The variation in the second and third basis functions (left) is expected:
  - variation low and high in the spectra caused by the sensor
  - variation in the middle caused by changes in the moss
- Sample with the maximum error is *very accurate below 700 nm* (right bottom)

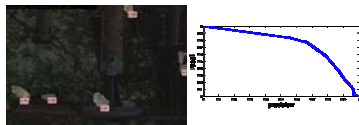


Photosynthesis begins to occur 5 minutes after being hydrated



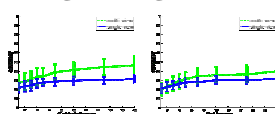
### Bird species catalog Detecting

- Goal:** Ecologists want to know the changes in bird species to a particular ecosystem
- Obstacles:**
  - There are no available direct sensors
  - Methods suggested by previously ecological studies have insufficient spatial/temporal resolution



- A background model is constructed by incorporating both the spatial and temporal variation.
- Classify a pixel as foreground based on the discrepancy of the color values of its spatial neighborhood relative to the background model.

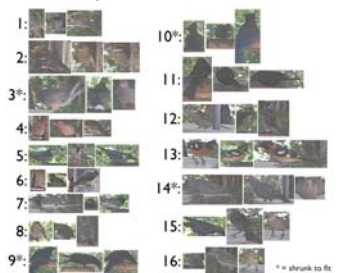
### Categorizing



- Group overlapping detections (in time) as a single object and treat each detection as a view.
- Cluster based on the following discrepancy measure:

$$D(H_c, H_b) = \max \left( \frac{1}{|H_c|} \sum_{a \in H_c} \max_{b \in H_b} d(a, b), \frac{1}{|H_b|} \sum_{b \in H_b} \max_{a \in H_c} d(a, b) \right)$$

### Publicly Available Dataset



<http://vision.cs.ucla.edu/~tko>