Modern Global Oxygen Production

Distribution of global, shallow, warm water coral reefs in 2010

Value
- Shoreline protection
- Economic value
- Highest biodiversity
- Medical applications

Pressures
- Climate Change
- Ocean Acidification
- Pollution, run-off
- Human Impact

Data: Scripps Oceanographic Institute, NOAA, NASA, UNEP
Effective Spatial Resolution [m]

- 1cm
- 10cm
- 50cm
- 1m
- 10m

MiDAR UAV

Satellite
## NOVEL INSTRUMENT TECHNOLOGIES

**Science**

| Physical oceanography, understand shallow coastal environment, transport, flow and storm surge |
|__________________________________________________________________________________________|
| Biological oceanography, determine health, extent and coverage of marine life |

**Remote Sensing Measurements**

| Bathymetry, sea surface temperature, salinity |
|__________________________________________________________________________________________|
| High-resolution, multispectral image of underwater environment |

**Technologies**

| FluidCam |
| MiDAR |
2D Fluid Lensing Results, Coral Image Test Target, Test Platforms 11, Depth = 4.5m, MSL

No Fluid

Raw Distorted Frames

2D Fluid Lensing Results

Flat Fluid

Mean Image (600 frames)

2D Fluid Lensing Integration (90 frames)
FluidCam 1&2 offer more than a 10x improvement over previous Fluid Lensing instruments in resolution, data bandwidth, spectral range, SNR, and onboard compute capability.
MiDAR Transmitter - LED Array

MiDAR Receiver - FluidCam NIR

MiDAR Multispectral Reconstruction

N-channel, narrowband structured illumination, $\varphi_{\text{LED}}(P,t)$ and embedded data stream at $bN/r$ bits/s

Panchromatic high-frame-rate computational imager records frames $I(x,y,t)$

Automated MiDAR color signature identification $\varphi_{\text{color}} = \text{NIR}, \text{R}, \text{G}, \text{B}, \text{UV}, \ldots$, ambient radiance calibration, intensity normalization and embedded data decoding

Multispectral Video

Data Transmission

3D Structure
MACHINE LEARNING WITH FLUIDCAM & MIDAR
Sand/Other
Branching
Mounding
Rock
FL + SFM Depth
Best Satellite Image
Fluid Lensing on UAV
Manual ID
Automated Morphology ID
Automated Percent Cover ID

8% total error in Morphology ID
5% total error in Percent Cover ID vs 30% in literature

Living Structure
Nonliving Structure

8% total error in Morphology ID
5% total error in Percent Cover ID vs 30% in literature
How to use high resolution data to augment low resolution imagery?
Is there a method to autonomously relate these feature spaces?

**Goal:** To use high resolution data from UAVs augment low resolution datasets captured by higher altitude and satellite platforms.
Leverage airborne data, which offers high resolution imagery of reef systems close to the source which gives the best representation of the feature space.

**Idea:** Leverage airborne data, which offers high resolution imagery of reef systems close to the source which gives the best representation of the feature space.

**Concept:** Train UAV dataset against the reference dataset using supervised machine learning. Take this classification criteria and apply it to a transformed version of the satellite dataset.

**General Approach**

1. **Satellite dataset**
2. **Airborne dataset**
3. **Reference Dataset**

- **Image Rectification**
  - Align satellite and airborne datasets

- **Machine Learning (ML) Training**
  - Train UAV data against reference
  - Use ML solution on analogous feature spaces as produced by satellite datasets

- **Prediction**
  - Transform satellite dataset accordingly
  - Use previous ML classification to predict upon satellite datasets
  - Look at misclassification and accuracy
Image Rectification

- Align images and resolutions:
- Scale Invariant Feature Transform (SIFT)
- Random Sample Consensus (RANSAC)
- Finds the optimal homography transform
Augmented Machine Learning Training

Reference Data

PCA + SVM

SVM Classification Result

**PCA**

\[ x_{PCA} = \begin{bmatrix} p_1^T \\ p_2^T \\ \vdots \\ p_n^T \end{bmatrix} (x_{\lambda} - x_{\lambda,\mu}) \]

- \( x_{PCA} \): Data point in PCA space
- \( p_i^T \): \( i \)-th principal unit vector
- \( x_{\lambda} \): Data point in original space
- \( x_{\lambda,\mu} \): Mean of \( x_{\lambda} \)

**SVM**

- 3rd order polynomial SVM fit to \( x_{PCA} \)
- Separation into \( k \) classes via one-versus-one classification
Prediction Methodology

Augmentation Algorithm:

1) **Partition** image into various sections

2) **Translate**, **rotate** and **scale** auxiliary dataset with reference to original SVM solution
   - **Translate**: Determined by mean of classes
   - **Rotate**: Determined by PCA directions
   - **Scale**: Determined by covariance of classes

3) **Predict** upon partitioned image using previous SVM solution
   - **Repeat** over all partitions
   - **Overlap** areas to build **Consensus**
Gradient analysis (2 class)

- Identify regions of high gradients
- Perform clustering by DBSCAN
- Assign labels on adjacent points in relation to clustered points

Translate

Rotate by mapping onto PCA vectors

Scaling
Scale by covariance matrix
Results: 2-m scale Imagery

Coral Cover

Reference

K-means

Direct SVM

Augmented

~66% Accuracy

~69% Accuracy

~71% Accuracy

Morphology

Direct SVM

Augmented

~50% Accuracy

~57% Accuracy
Robustness

What if we learn upon an entirely different region?

1) Take MAP estimate as reference
2) Learn upon these data
3) Predict on original transect

Coral Cover Prediction Accuracy

<table>
<thead>
<tr>
<th>Method</th>
<th>0.3 m</th>
<th>0.5 m</th>
<th>2 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-Means</td>
<td>67%</td>
<td>71%</td>
<td>66%</td>
</tr>
<tr>
<td>SVM</td>
<td>74%</td>
<td>74%</td>
<td>63%</td>
</tr>
<tr>
<td>Previous Augmented</td>
<td>84%</td>
<td>79%</td>
<td>71%</td>
</tr>
<tr>
<td>Augmented</td>
<td>83%</td>
<td>77%</td>
<td>69%</td>
</tr>
</tbody>
</table>

Morphology Prediction Accuracy

<table>
<thead>
<tr>
<th>Method</th>
<th>0.3 m</th>
<th>0.5 m</th>
<th>2 m</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVM</td>
<td>59%</td>
<td>61%</td>
<td>38%</td>
</tr>
<tr>
<td>Previous Augmented</td>
<td>69%</td>
<td>62%</td>
<td>57%</td>
</tr>
<tr>
<td>Augmented</td>
<td>70%</td>
<td>68%</td>
<td>60%</td>
</tr>
</tbody>
</table>
Classification of Coral Cover

1 cm

UAV Fluid Lensing

30 cm

Vexcel UltraCam

Pleiades 1-A

and (2) discrimination by morphology (sand, rock, branching coral, or mounding coral). The method is based upon Principal Component Analysis (PCA) to remap and rescale existing datasets upon a known Support Vector Machine (SVM) solution within analogous principal spaces. This supervised method is able to autonomously compensate for changing water depth and illumination conditions, with errors for coral cover and morphology classification derived from aerial imagery at approximately 16% and 31%, respectively. Classification error for data derived from the highest resolution commercial satellite imagery available (Pleiades-1A) is approximately 21% for coral cover and 38% for morphology. Although classification accuracy is improved across both phases, morphology discrimination suffers more acutely from lower resolution and noise effects. However, the method shows promise for future work where UAVs may observe multispectral or hyperspectral data, further increasing the speed and accuracy of classification and enhancing datasets taken at higher altitudes.
Airborne MiDAR-UV

Wavelength, $\lambda$ [nm]

FluidCam NIR Q.E., $\eta$ [quantum [%]]

Multispectral Mapping  Atmospheric Correction  Mineral Detection  Underwater Imaging
other approaches include use of standard supervised learning methods such as nonlinear embedding (MDS, Isomap) in combination with an optimization routine at each layer of the deep network for structure learning on the unlabeled pool (Weston, Ratle, Mobahi, & Collobert, 2012).

3.) Augmenting labeled data through active learning.

Active learning is an area of machine learning research that uses an “expert in the loop” to learn iteratively from large data sets that have very few annotations or labels available. In our case, the users classifying objects are humans in the loop and the active learning strategy algorithm decides which sample from the unlabeled pool should be given to the expert for labeling such that the new information obtained is most useful in improving the classifier performance on the unlabeled/unseen data. Common strategies include...
THANK YOU!
Morphology and Percent Cover Error vs. Effective Spatial Resolution

- Morphology ID Error
- Percent Cover Error

Fluid Lensing Required

$R^2 = 0.936$

$R^2 = 0.924$

1cm 10cm 1m 10m 100m

Effective Spatial Resolution [m]

40% SHOCK!!!

MiDAR UAV

Pleadies-1A

LandSat 8

Resolution 1mm 1cm 10cm 1m 10m 100m

MiDAR UAV

FluidLens Required

LEO CubeSat
Automated Percent Cover ID

- Sand/Other: 43%
- Branching: 18%
- Mounding: 36%
- Rock: 3%

Automated Morphology ID

- Sand/Other: 36.0%
- Branching: 18.0%
- Mounding: 36.0%
- Rock: 3.0%

Automated Reef Morphology ID

- Rock: 3.0%
- Sand/Other: 43.0%
- Mounding: 36.0%
- Branching: 18.0%
FluidCam & MiDAR
Fused Machine Learning & Dataset Augmentation

+ Cm-scale dataset infusion
+ Enhanced classification

NASA AMES
LABORATORY FOR ADVANCED SENSING

NASA
Results: 0.3-m scale Imagery

Coral Cover

K-means: ~67% Accuracy
Direct SVM: ~83% Accuracy
Augmented: ~84% Accuracy

Morphology

Direct SVM: ~52% Accuracy
Augmented: ~69% Accuracy
Results: 0.5-m scale Imagery

Coral Cover

- K-means: ~71% Accuracy
- Direct SVM: ~78% Accuracy
- Augmented: ~79% Accuracy

Morphology

- Direct SVM: ~61% Accuracy
- Augmented: ~62% Accuracy
labels by maximizing the class probabilities of the unlabeled data pool (Lee, 2013). Other approaches include use of standard supervised learning methods such as nonlinear embedding (MDS, Isomap) in combination with an optimization routine at each layer of the deep network for structure learning on the unlabeled pool (Weston, Ratle, Mobahi, & Collobert, 2012).

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- NeMO-Net, Chirayath et al.
- NASA ROSES AIST 2016 Proposal

Our lab has developed an active learning platform on tablet and virtual reality platforms, where users can view 3D FluidCam data of coral reefs and provide training data on coral classes including living cover, morphology type, and species identification. The se data, along with their spatial coordinates, are fed into NeMO-Net, which produces a classification map and reef constituent breakdown as well as error analysis. This technology has already been developed at LAS for visualization and interaction with FluidCam 3D coral reef data and will be expanded to NASA CORAL data as well.

The proposed CNN learning module will have access to other useful services such as geolocation, layered data, and other classification tools for comparison to our methodology. The Python package will also be designed to build upon and integrate with existing libraries for machine learning and modern geospatial workflow, such as TensorFlow, Scikit-learn, Rasterio, and Geopandas. To increase computational speed, NeMO-Net will take advantage of GPU processing on the LAS Laika compute cluster as well as the High-End Computing Capability (HECC) Pleiades supercomputing cluster. The active learning application will be developed on the game development platform Unity Pro and 3D modeling software Maya LT for iOS, with an interim Amazon server for data storage. All implementable software packages will be uploaded to the NASA Earth Exchange (NEX) repository, which currently houses many existing algorithms and data products related to machine learning and Earth Science. A high-level implementation of both software and hardware is shown in Figure 8.

For an overview of licensing and hardware specifications, refer to Table 2. All final code developed on all platforms as well as final deliverables will be made publicly available under the GNU General Public License (GPL).