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Change Detection of Marine Environments Using Machine Learning

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NPS NRP Executive Summary

Change Detection of Marine Environments Using Machine Learning
Report Date: 10/15/19 Project Number (IREF ID): NPS-19-M020-A
Naval Postgraduate School Graduate School of Engineering & Applied Sciences
Department of Oceanography



NAVAL RESEARCH PROGRAM

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

CHANGE DETECTION OF MARINE ENVIRONMENTS USING MACHINE LEARNING

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EXECUTIVE SUMMARY

Project Summary

Machine learning (ML), specifically deep learning (DL) using convolutional neural networks, is an increasingly powerful tool for classification of complex systems, including visual images and multispectral data. The focus of this study is to implement ML algorithms for 1) littoral environment classification and 2) change detection of littoral environments in order to rapidly assess changes in water quality, such as debris and oil slicks. Specifically, small unmanned aerial systems (UAS) were used to acquire data, including visual red-green-blue (RGB), RedEdge, near infrared (NIR) and infrared (IR), locally to Monterey Bay in order to train a deep neural network to recognize littoral environments on land, such as beach, marsh, and rocks, as well as water bottom type, such as sand, rock, and vegetation/algae. This database of images collected from UAS and small aircraft was used to assess coastal areas near ephemeral rivers that are known to seasonally breach thereby changing the littoral environment and water quality through erosion/removal of vegetation as well as sediment suspension. The remote sensing images were validated by site observations as well as morphodynamic observations of beach change in order to quantify the aerially observed changes. Results of ML model training indicate highly accurate (>90%) detection of littoral environments, both over land and littoral waters, without any need for image segmentation. These findings suggest models for targeted areas could be developed for rapid and accurate change detection post extreme events (hurricanes/tsunamis).

Keywords: *Machine learning, ML, deep learning, DL, littoral environments, change detection, unmanned aerial systems, UAS, red-green-blue, RGB, near infrared, NIR, infrared, IR, remote sensing*

Background

Landscape classification in coastal environments is a sub-discipline of large-scale landscape or land-use classification techniques involved in many areas of geospatial information analysis. Recently, ML algorithms have been implemented with heterogeneous landscapes to provide pixel-level classification of imagery (e.g. Buscombe and Ritchie, 2018; Maggiori, et al., 2017; Salamati, et al., 2012). However, the generation of ML models that are capable of pixel classification require carefully curated images with class delineations. While this method offers decent results for test images, it is not easily transferrable to datasets that have not been hand-labeled at the pixel level or have a wide range in field of view (or other image characteristics). In contrast to pixel-level classification, this study proposes traditional image classification for heterogeneous coastal environments in order to provide a model that is widely applicable to global coastal environments.

Aerial imagery, collected either by UAS or small aircraft, provides high-resolution (spatial and temporal) monitoring of coastal marine areas. This data can be used to identify and classify specific marine environments and visual changes in water quality, with the goal of creating a neural net that can then be used for assessment of marine environment changes. Specifically, local California coastal areas were used as proof-of-concept to identify regions including kelp forests, sandy bottom habitats, and reef/rocky bottom habitats. This approach could be applied to remote marine areas including Pacific National Monuments and missile test ranges with the intent of providing efficient management practices for these difficult-to-patrol areas. This project was a collaboration with the United States Coast Guard Research and Development Center.

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The research questions are:

1. Can littoral environment and water quality and bottom type be determined by a neural network image feature extraction method?

Hypothesis 1: Provided sufficient data, deep neural networks are capable of identifying different littoral environments to high accuracy (>90%).

2. Can an algorithm be created that automates an assessment of change or damage at high-risk coastal assets?

Hypothesis 2: Using the trained neural networks from Hypothesis 1, it is possible to combine predictions from two identical regions but at different times into a single map indicating regions of greatest change.

Findings and Conclusions

This project was a proof-of-concept endeavor to address ML capabilities, weaknesses, and applications in landscape classification of littoral environments. The first task was to compile a nearshore coastal waters database to expand upon an existing database for sub-aerial coastal zones (beach, marsh, tidal flat, etc.) that is used for change detection of the coast. This project also included adding IR images of similar coastal classes to enhance the database. This database provided the required input data to train thirteen DL neural networks in image feature recognition using RGB imagery only. The purpose of this extensive model training was to determine which model architectures were capable of classifying littoral environments. Model accuracies were all above 90% accurate, suggesting that hypothesis 1 is well-supported. Further assessment of varying littoral water environments would be useful to expand the existing data.

The second task was to acquire new data over littoral waters with the 5-channel (RGB, NIR, RedEdge) camera that was fitted to the principal investigator's UAS. This database spans five littoral classes (beach, coastal rocks, sandy bottom, rocky bottom, and kelp/vegetation), and a new artificial intelligence model is being developed (LCDR Mielke's thesis) using training from scratch as well as transfer learning to determine the best possible method for heterogeneous coastal classification of littoral waters using 5-band imagery.

The third task of this project was to create large-scale mapped areas of coastal assets to provide a baseline status check for vulnerable and high-impact areas. Specifically, the Carmel River State Beach was used as a local site known for change. After an extreme flooding event (beach breaching), the same area was surveyed to assess impact using coastal change detection through the convolutional neural network tested on the generated database (Capt. Ayoub's thesis). A longer-term goal is establishing a method to identify high-risk coastal sites based on fundamental change in environment (such as beach breaching, damage to buildings).

The overall goal of this project was to determine the feasibility and usefulness of DL methods for littoral environment classification and change detection. The first phase of conclusions suggest that model accuracies are capable of classifying littoral environments. The second phase of research is still ongoing as it is student led. The research to date is included as two ongoing theses for students set to graduate December 2019 and March 2020.

- LCDR Ash Mielke: curation of littoral database. Development of littoral classification models will be completed by 12/2019.
- Capt. Teddy Ayoub: Development of change detection algorithms using Siamese networks is ongoing, to be completed by 03/2020.

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Recommendations for Further Research

Given the preliminary success of multiple DL architectures for classification, a longer-term goal is to establish an easy-to-use and automated methodology to detect change and damage to coastal high-impact assets. By creating an DL-driven assessment of coastal change, a time-efficient and consistent method will be created capable of assessing any coastal feature and performing a change detection to determine fundamental changes in environment.

Specifically, it is recommended that an expansive dataset be curated to expand upon the California dataset so that model capabilities are not region specific. This will require further testing/training of neural network architectures, but will help solidify accuracies and transferability.

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Acronyms

Deep Learning	DL
Infrared	IR
Machine Learning	ML
Near-Infrared	NIR
Red-Green-Blue	RGB
Unmanned Aerial System	UAS