National Aeronautics and Space Administration

Applying machine learning to mapping of small-scale ocean features using both SAR and sea surface temperature data

Principal Investigator: Benjamin Holt (329)
Brian Bue, Jinbo Wang (329)

Program: Spontaneous Concept

Project Objective:
The objective of this proposal is to develop methods using machine learning (ML) to demonstrate a proof of concept system to automatically identify small ocean eddies from both synthetic aperture radar (SAR) and optical derived sea surface temperature (SST) imagery. This was done using training data of small eddies detected in both sensor streams, obtained from data acquired along the California coast.

FY18/19 Results:
We used the extracted SAR and SST eddy ROIs to construct Convolutional Neural Network (CNN) models trained to distinguish ROIs containing eddies from ROIs without eddies. Conventional CNN models require much more labeled data than we have available to train from scratch, so we used a widely used approach called transfer learning to leverage CNN models “pre-trained” on large image databases. Using the available labeled data to refine pre-trained CNNs permits more accurate results when labeled data is scarce. We used three-fold cross validation to partition our available data into training and test sets, and evaluated test prediction accuracy using pre-trained models refined independently on each of the SAR and SST data sets, observing 75% precision and 64% recall on the SAR data, and 78% precision, 52% recall on the SST data. While the true positives and negatives are typically distinguishable in the SAR observations, the mispredictions (false positives and negatives) are often highly ambiguous – notably, most of the SAR false positives shown in the figure are visually similar to eddies. The SST observations are more ambiguous than the SAR observations due partially to their lower spatial resolution, but also as a result of less discriminative spatial patterns.

Benefits to NASA and JPL: Although our initial results are far from an operational system, they provide initial evidence that automated eddy detection is feasible with both SAR and SST observations, even with very little available labeled training data. Combining the two modalities can enable multi-asset “detect and confirm” follow-up operations which will increase detection confidence/reduce false positives. We also demonstrate that combining SAR and SST eddy detection models both improves detection accuracy and provides higher confidence predictions in comparison to SAR-only or SST-only eddy detectors. Further efforts with additional training data and examination of another ocean region are needed to enhance this ML concept, With the steady stream of SAR imagery from Sentinel-1AB plus multiple SST sensors including Sentinel-3, more efficient techniques are called for to enhance the utility of these growing data sets in studies of ocean circulation dynamics and mixing, particularly on these smaller-scales, such as defined as an objective of the SWOT mission**.**

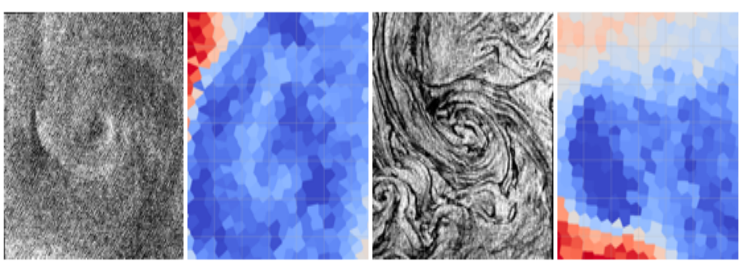

Figure 1. Representative examples of two Sentinel-1 SAR cyclonic eddies plus coincident sea surface temperature (SST) images. Notice the spiral nature and details of the eddies seen in the SAR imagery and the expected cold water (blue) signatures in the central core region of the Sentinel-3 SST data. One expected outcome using ML-identified eddies in both SAR and SST, is to evaluate the appearance of the SAR and the temperature contrast within the eddy, which may be indicative of duration since generation.

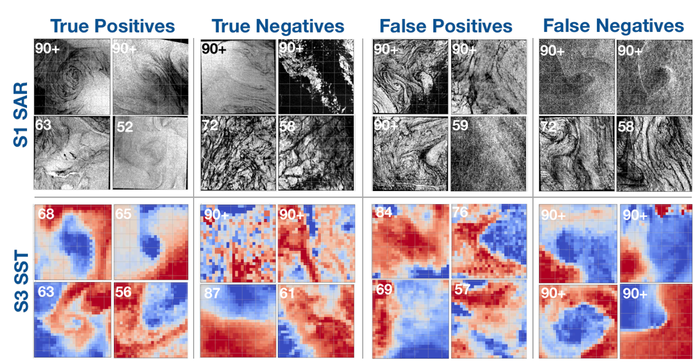

Figure 2. Example S1 SAR (top) and S3 SST (bottom) ROI eddy predictions. Prediction confidence values are provided in the upper left corner of each ROI.

Publications:
Holt, B., B. Bue, J. Wang (2020) Mapping of small-scale ocean features using both SAR and sea surface temperature data with machine learning, AGU Ocean Sciences Meeting, Feb. 2020, submitted

Contact Info:
Ben Holt
818-354-5473
benjamin.m.holt@jpl.nasa.gov

National Aeronautics and Space Administration
Jet Propulsion Laboratory
California Institute of Technology
Pasadena, California

www.nasa.gov

R19240 Poster No.