Imperial College London
Department of Earth Science and Engineering
MSc in Environmental Data Science and Machine Learning

Independent Research Project
Project Plan

Evaluating the ability of Self Supervised Learning to identify Submesoscale atmospheric processes using Wave-Mode SAR Data

by
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Abstract

The ocean plays a vital role in regulating Earth's climate, making detailed observations of its surface essential. Sentinel-1's Wave Mode (WV), designed for ocean wave monitoring, captures over 120,000 synthetic aperture radar (SAR) image vignettes monthly, offering a rich but underutilised dataset of oceanic and atmospheric phenomena. While WV effectively detects sea surface roughness and geophysical processes, its full potential remains limited by the lack of automated tools for classification. Traditional supervised learning methods require manual labelling, this process is labour intensive, inefficient and expensive. This project investigates the use of self-supervised learning (SSL) as an alternative approach to identifying processes in SAR WV imagery without the need for annotated datasets. SSL uses data augmentation and contrastive learning to train a model to distinguish between different images and recognise invariant features across augmented views of the same image. A convolutional neural network (CNN) architecture will be used to embed augmented SAR images into a semantic space, allowing the model to learn meaningful representations directly from the data. The objective of the research is to assess whether SSL can effectively learn meaningful features directly from Sentinel-1 WV imagery, providing a foundation for future unsupervised classification of ocean–atmosphere interactions, in order to better understand the role of the ocean in regulating the Earth's climate.

Introduction

The ocean plays a central role in Earth's climate system, acting as a major regulator of global energy and water cycles. The ocean surface, in particular, serves as the interface for the exchange of heat, moisture, and momentum between the atmosphere and the ocean. Comprehensive measurements of this interface are essential for understanding ocean-atmosphere interactions and for the development of high-resolution climate models (Topouzelis & Kitsiou, 2015). Remote sensing is a key tool for observing the Earth's surface and monitoring changes in the climate system. It can be broadly divided into two categories: passive sensing, which relies on external energy sources such as sunlight, and active sensing, which uses its own energy source (Yang et al, 2013).

This research focuses on spaceborne Synthetic Aperture Radar (SAR), a form of active remote sensing capable of acquiring high-resolution sea surface backscatter data regardless of weather or lighting conditions (Yee Kit Chan et al, 2013). SAR can be modulated by a range of physical process including ocean swell (Collard et al, 2009), upper ocean processes (Jia et al, 2019) and atmospheric phenomena (Alpers et al, 2016), making it a perfect tool to capture ocean-atmosphere interactions. Of particular interest for this research is Sentinel-1's Wave mode (WV) which captures 20×20 km SAR image vignettes at alternating incidence angles of 23° and 37°, with a ground resolution of approximately 4 meters. These vignettes are acquired every 200 km along the satellite's ground track (ESA, 2014).

WV images exhibit oceanic and atmospheric structures that typically span 1 to 10 km (submesoscale features) which aid in the understanding of small-scale ocean–atmosphere interactions. However, these features are often too small and short-lived to be effectively captured by traditional oceanographic sensors. The high spatial resolution of Sentinel-1's WV enables these phenomena to be observed in unprecedented detail (Wang et al, 2019). Figure 1 illustrates examples of these submesoscale patterns, highlighting the value of SAR WV imagery for investigating mesoscale and submesoscale dynamics in the marine environment taken from the open source TenGeop dataset.

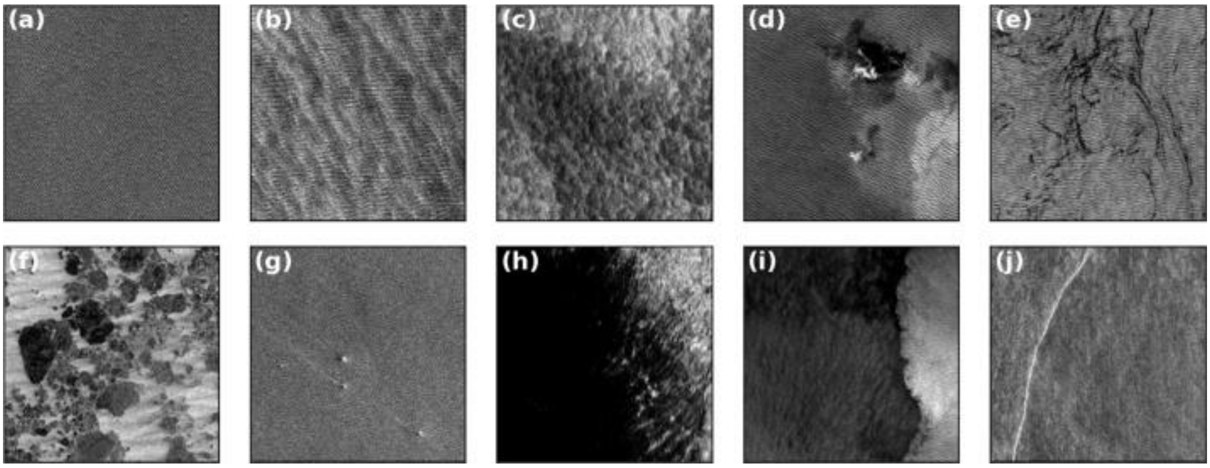

Fig. 1. Ten vignette examples of expertly-defined geophysical phenomena. From (a) to (j) are pure ocean waves (PureWave), wind streaks (WindStreak), micro convective cells (WindCell), rain cells (RainCell), biological slicks (BioSlick), sea ice (SeaIce), icebergs (IceBerg), low wind area (LowWind), atmospheric front (AtmFront) and oceanic front (OcnFront). (Wang et al 2018).

WV remains underutilised due to the lack of automated tools for detecting and classifying such features. Traditional classification methods rely on manual annotation, which is both time-consuming and inefficient (Yang et al, 2022). Deep learning has been widely applied to automate the classification of remote sensing data (X. Zhu et al, 2017). However, most existing models rely heavily on supervised learning, which requires large, manually labelled datasets. This presents a major challenge in the context of SAR imagery, where high-quality annotations are scarce and costly to produce. This project explores an alternative approach to manually labelling data. This computational approach uses Self-supervised learning (SSL), a branch of unsupervised learning in which a neural network is trained to learn meaningful data representations from the data itself (Gui et al, 2024). In SSL, input images are distorted through a set of semantic-preserving augmentations and then passed through an encoder network (typically a CNN) to produce embeddings. Contrastive learning techniques are used to train the model by bringing embeddings of different augmented views of the same image closer together, while pushing embeddings of different images further apart in the representation space (Jaiswal A, et al 2021). Although SSL is a relatively new approach in the SAR domain, it holds significant promise given the limited availability of annotated data.

This project aims to evaluate whether self-supervised techniques can effectively learn meaningful features directly from Sentinel-1 WV imagery, without the need for supervision. This could allow for the analysis of ocean-atmospheric interactions on a larger and more cost effective scale, and ultimately improve environmental monitoring and our understanding of the changing climate system.

Methodology

Phase 1: Data augmentation through contrastive learning

In this phase, the focus will be on designing and implementing effective data augmentation strategies fit for self-supervised contrastive learning on SAR WV imagery. Since the success of contrastive self-supervised learning relies heavily on the quality and diversity of augmentations, this step involves reviewing modern methods of contrastive learning (e.g., SimCLR) and adapting them using domain-specific knowledge of WV imagery. Augmentations such as geometric transformations, noise injection, and resolution alterations may be used with the aim of preserving the core geophysical features and encouraging the model to learn invariant representations. The goal is to produce image pairs that allow the contrastive loss to pull augmented views of the same image closer in the representation space while pushing apart unrelated images.

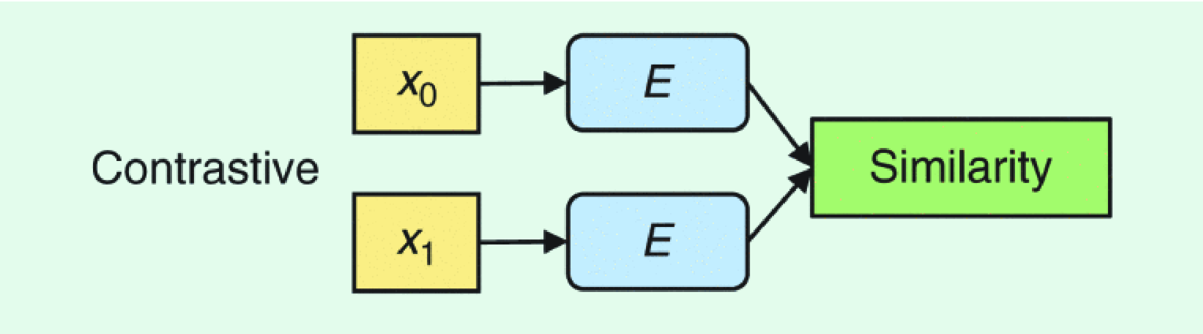

Figure 2: basic underlying concept of contrastive learning (Wang et al, 2022).

Phase 2: Design embedding software

This phase involves the development of a simple convolutional neural network (CNN) architecture to serve as the base embedding model for the self-supervised learning architecture. Its function is to transform augmented SAR images into meaningful low-dimensional embeddings that capture essential features relevant to oceanic and atmospheric phenomena. Throughout this project, the architecture will be evaluated and improved based on training performance and results from downstream tasks. This approach ensures that the model evolves to better capture the complex patterns present in the WV imagery while remaining computationally manageable.

Phase 3: Downstream tasks

Once the self-supervised learning (SSL) model has been trained, an evaluation will be conducted to assess the quality of the learned representations. This will include a series of unsupervised analyses such as clustering (e.g., k-means or DBSCAN) applied to the embedding space to determine whether semantically similar SAR images are grouped together. Dimensionality reduction techniques such as t-SNE or UMAP will be used to visualise the structure of the embedding space and provide insights into feature separability. A manually labelled data set could potentially also be introduced, in which classification such as k-nearest neighbours (k-NN) can be performed to assess the performance of the learned features.

Progress to date

Data preprocessing - As part of the initial phase of this project, Sentinel-1C satellite imagery was selected to ensure the use of the most up-to-date data. Data was gathered across a larger geographic area within a shorter time window, in order to capture a wider variety of physical features such as ice caps, sea ice, and open ocean conditions. Additionally, preliminary visualisation of the imagery has been carried out, both to assess data quality and for the development of augmentation strategies that will be used in the training phase.

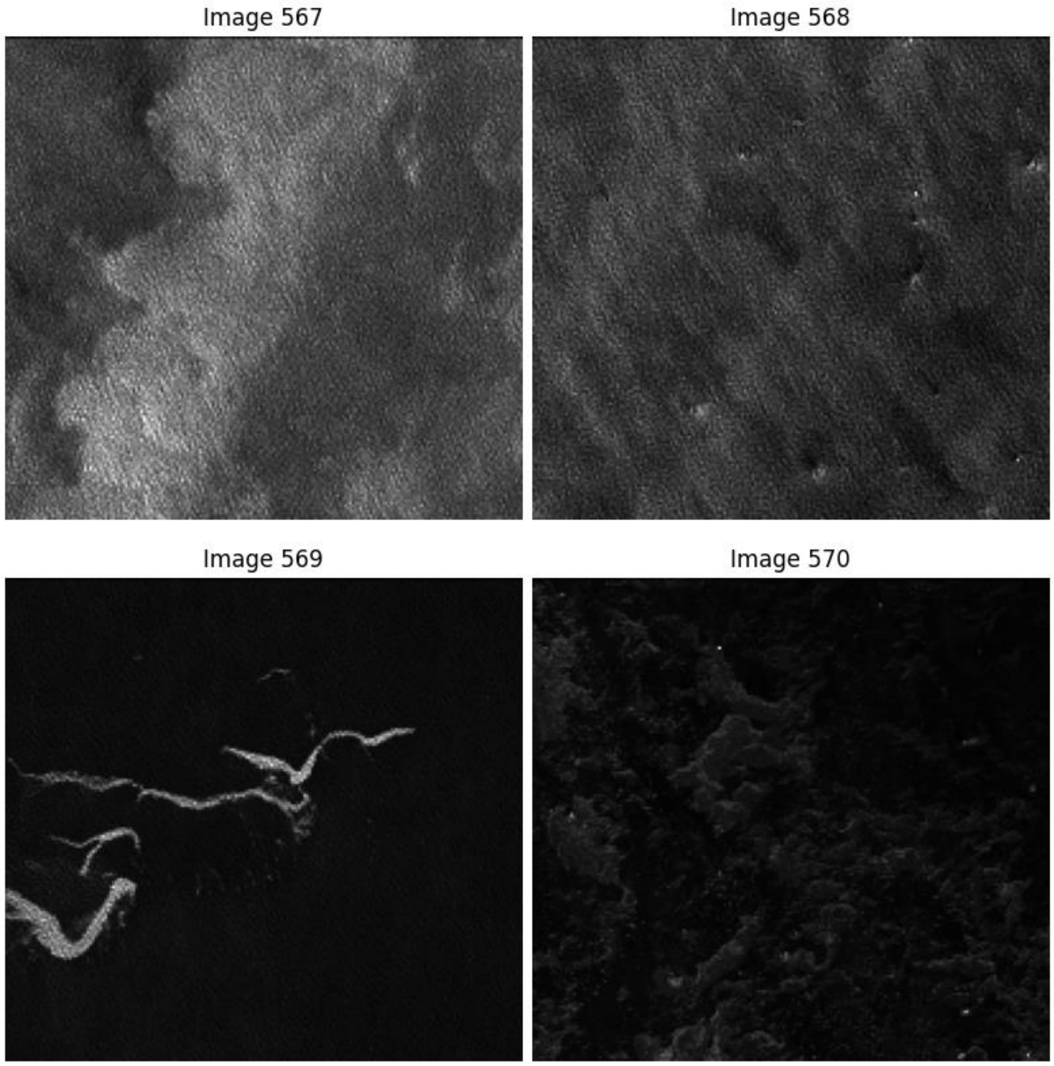

Figure 3: Sample of pre-processed images from the dataset with unlabelled geophysical features present.

Future Plan

Estimated timeline

Phase	Weeks	Tasks
Initial Setup	1-2	Conduct literature review and create project plan
Design baseline model	3	Build and test an initial, functioning self-supervised model architecture
Model improvement	4-5	Enhance model depth, architecture and embedding quality
Model evaluation metrics and finetuning	6-9	Evaluate model performance, conduct hyperparameter tuning, visualisation
Report writing	10-12	Final analysis, Write report, package code, and review literature

Table 1: Estimated timeline of project

Citations

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AI usage:

Chatpgt-4o

OpenAI

DINO with CNNs

Used for understanding of CNN and SSL on top of the provided lectures and scientific paper resources provided by the university.

All committed work is my own, AI was used only for my own personal understanding of the topic.