Surface drifter trajectory prediction in the Gulf of Mexico using neural networks

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Abstract

Machine learning techniques are applied to Lagrangian trajectory prediction, which is important in oceanography for providing guidance to search and rescue efforts, forecasting the spread of harmful algal blooms, and tracking pollutants and marine debris. This study evaluates the ability of two types of neural networks for learning ocean trajectories from nearly 250 surface drifters released during the Grand Lagrangian Deployment in the Gulf of Mexico from Jul-Oct 2012. First, simple fully connected neural networks were trained to predict an individual drifter's trajectory over 24 h and 5 d time windows using only that drifter's previous velocity time series. These networks, despite having successfully learned modeled trajectories in a previous study, failed to outperform common autoregressive models in any of the tests conducted. This was true even when drifters were pre-sorted into geospatial groups based on past trajectories and different networks were trained on

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each group to reduce the variability that each network had to learn. In contrast, a more sophisticated social spatio-temporal graph convolutional neural network (SST-GCNN), originally developed for learning pedestrian trajectories, demonstrated greater potential due to two important features: learning spatial and temporal patterns simultaneously, and sharing information between similarly-behaving drifters to facilitate the prediction of any particular drifter. Position forecast errors averaged around 60 km at day 5, roughly 20 km lower than autoregression, and even better for certain subsets of drifters. The passage of Tropical Cyclone Isaac over the drifter array as a tropical storm and category 1 hurricane provided a unique opportunity to also explore whether these models would benefit from adding wind as a predictor when making short 24 h forecasts. The SST-GCNNs were found to not benefit from wind on average, though certain subsets of drifters (based on deployment) exhibited slightly lower forecast errors at hour 24 with the addition of wind.

Keywords: advection, current velocity, mass transport, Lagrangian motion, current prediction, machine learning

1. Introduction

Ocean trajectory prediction is a notoriously difficult problem. Most notably, the unsteady nature of oceanic flows often leads to chaotic advection (*e.g.*, Aref, 1984; Yang and Liu, 1997; Özgökmen et al., 2001; Koshel' and Prants, 2006), requiring that initial conditions be known with considerable accuracy in order to properly initialize forecast models. At the same time, the minimum number of points in time and space that must simultaneously be sampled or numerically resolved in order to capture the full complexity of 3-D ocean dynamics are on the order of 10^{23} (Stommel, 1948; Holland and Lin, 1975a,b; Özgökmen et al., 2009). With observational data density nowhere near this threshold and with model resolutions restricted by computational resource limits, existing prediction tools lack the fidelity necessary for predicting chaotic ocean behavior (Özgökmen et al., 2009; Bolton and Zanna, 2019). Nevertheless, many high-stakes applications such as oil spill response (Poje et al., 2014; Özgökmen et al., 2016), search and rescue operations (Isaji et al., 2006; Serra et al., 2020), and forecasting the spread of harmful algae blooms, pollutants, and marine debris (Enriquez et al., 2010; Olascoaga, 2010; Olascoaga and Haller, 2012; Normile, 2014; Coulin et al., 2017; Lermusiaux et al., 2019) rely on ocean forecasting.

Existing approaches to ocean forecasting include data-assimilating ocean models (Coelho et al., 2015; Wei et al., 2016; van Sebille et al., 2018) and statistical stochastic models (Griffa, 1996; Berloff and McWilliams, 2003; Lermusiaux and Lekien, 2005; Haza et al., 2016; Feppon and Lermusiaux, 2018; Lu and Lermusiaux, 2021). The problem of sparse ocean data plagues both techniques. Ocean general circulation models (OGCMs) such as the