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Deep Learning for Lagrangian Drift Simulation on Sea Surface

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Introduction

The simulation of Lagrangian trajectories on the ocean surface is important for various application domains including monitoring plastic and debris movement [Maximenko et al., 2012], investigating algae and plankton dynamics [Son et al., 2015], or trajectories forecasting crucial for search and rescue operations [Breivik et al., 2013]. Moreover, the study of Lagrangian drift allows to assess the capabilities of ocean numerical models in accurately representing small-scale dynamics [Barron et al., 2007, Botvynko et al., 2023]. Nonetheless, generating realistic trajectories on the sea surface presents a notable scientific challenge within the realm of operational oceanography [Röhrs et al., 2021].

Model-based methods for the numerical simulation of Lagrangian trajectories rely on a step-by-step advection procedure using sea surface velocity fields [Lange and van Sebille, 2017a]. Nevertheless, slight discrepancies in the underlying velocity fields or the use of velocity fields lacking fine spatial resolution can result in inaccurate Lagrangian trajectory modelling, rendering these methods impractical for operational applications.

Data-driven learning-based methods such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and generative models such as Variational Auto-Encoders (VAEs) or Generative Adversarial Networks (GANs), showed significant capacity in capturing spatio-temporal dependencies in simulated trajectories [Aksamit et al., 2020, Jiang et al., 2019, Jenkins et al., 2023, Julka et al., 2021, Dan, 2020]. However, only a restricted number of previous studies were applied to the conditional simulation of individual Lagrangian trajectories [Quinting and Grams, 2022].

Due to the limitations described above, this study aims to present an original Deep Learning framework, referred to as DriftNet, for the conditional simulation of individual trajectories on sea surface. The proposed model may be fed up with any geophysical field containing information on ocean dynamics and generates the trajectory of a drifting object on sea surface. DriftNet is fully convolutional and includes a spatially-explicit latent encoding of targeted trajectory, inspired by Eulerian Fokker-Planck formalism of a drift [Botvynko et al., 2023]. In this representation, the trajectory is derived through non-local feature extraction from the conditioning input fields, meaning that the dynamics of a simulated trajectory are modeled by considering the entire dynamics of the surrounding area.

Methods

Model-driven approaches implement explicit time and space integration schemes such as Runge-Kutta 4 in order to advect individual particles by the underlying flow. This leads to the following advection formulation :

$$\vec{r}(\vec{r}_0, t + \Delta t) = \vec{r}(\vec{r}_0, t) + \int_t^{t+\Delta t} \vec{v}(\vec{r}_0, \tau) d\tau \quad (1)$$

with $\vec{r}(\vec{r}_0, t)$ and $\vec{v}(\vec{r}_0, t)$ respectively the position and velocity at time t of the particle initially located at \vec{r}_0 . The local-wise nature of the equation (1) leads to the propagation of errors due to the unresolved underlying velocity fields [Callies et al., 2021].

In order to compensate this limited sequential representation, we explore the Eulerian formulation of Lagrangian dynamics through Fokker-Planck formalism [Visser, 2008], which allows to generalize eq.(1) to the time propagation of the Probability Density Function (PDF) of the moving particle as follows :

$$\frac{\partial}{\partial t} p_{\vec{r}}(x, t) = - \frac{\partial}{\partial x} [\mu(x, t) p_{\vec{r}}(x, t)] \quad (2)$$

where x represents spatial position in the Eulerian framework, t the time, $p_{\vec{r}}(x, t)$ the PDF of the particle at position \vec{r} and $\mu(x, t)$ a drift field. In our case, this drift term relates to the velocity field $\mathbf{u}(x, t)$ in the Eulerian framework. Solving eq.(2) relies on a time integration scheme from the initial PDF $p_{\vec{r}}(x, t = 0) = p_{\vec{r}_0}(x, 0)$.

Here, we focus on a spatial domain of interest \mathcal{D} and we define the associated sequence of velocity fields $\mathbf{u} = \{\mathbf{u}_{(t_0)}, \mathbf{u}_{(t_0+\Delta)}, \dots, \mathbf{u}_{(t_0+K\Delta)}\}$ from time t_0 to $t_0 + K\Delta$, where Δ is the time sampling and K number of time steps. In the same way, we define the trajectory of a particle as a time series of locations $\vec{r} = \{\vec{r}_{(t_0)}, \vec{r}_{(t_0+\Delta)}, \dots, \vec{r}_{(t_0+K\Delta)}\}$ in \mathcal{D} where $\vec{r}^{(t_0)}$ defines the initial position of the particle.

DriftNet, inspired by eq.(2), encodes an individual Lagrangian trajectory into the following representation:

$$\begin{cases} \mathbf{y} &= \mathcal{E}(\mathbf{u}, \mathbf{y}_0) \\ \vec{r} &= \mathcal{M}(\mathbf{y}) \end{cases} \quad (3)$$

where $\mathbf{y} = \{\mathbf{y}(t_0), \mathbf{y}(t_0+\Delta), \dots, \mathbf{y}(t_0+K\Delta)\}$ is a space-time-explicit latent embedding of \vec{r} , and \mathbf{y}_0 initial latent embedding to encode the initial position $\vec{r}^{(t_0)}$. The Eulerian neural operator \mathcal{E} computes the latent embedding \mathbf{y} given velocity conditions \mathbf{u} and initial representation \mathbf{y}_0 , as introduced in eq.(2). Then, the neural operator \mathcal{M} maps the latent representation \mathbf{y} to the targeted Lagrangian drift \vec{r} . As such, it aims at mapping a multi-dimensional tensor to a time series of locations in $\mathcal{D} : \mathcal{M} = \sum_{\vec{x} \in \mathcal{D}} \vec{x} \cdot y_t = \vec{r}(\vec{r}_0, t)$, where $\vec{x} \in \mathcal{D}$ and $y_t \in \mathbf{y}$, a sample of \mathbf{y} at a time step $t \in [t_0, \dots, t_0+K\Delta]$.

The architecture of the operator \mathcal{E} is built as follows: given input meridional and zonal components of \mathbf{u} and initial condition \mathbf{y}_0 a 2D convolutional layer increases the number of channels from 3 to 64, followed by a LeakyReLU activation function; followed by a 2D convolutional LSTM block and a final 2D convolutional layer decreasing the number of channels from 64 to 2, followed by a 2 dimensional Softmax function.

Results and Discussion

We performed two experiments to evaluate the capabilities of DrifNet to generate realistic Lagrangian trajectories. The first (A) was performed in controlled numerical scenario, while the second experiment (B) concerns a real-use case.

The first experiment (A) explores how DrifNet can generate trajectories from partially-observed data in a fully-controlled virtual framework. In order to build the ground-truth trajectories database, we first advected virtual particles homogeneously distributed in space and time all over the case-study area of North East Pacific using numerical advection tool Ocean Parcels [Lange and van Sebille, 2017b] conditioned by fully known velocity fields called Nature Run [Benkiran et al., 2021]. DrifNet was then fed with partially-observed velocity fields, from Observation System Simulation Experiment (OSSE) framework [Tchonang et al., 2021], and trained to reproduce the ground-truth trajectories. The second experiment (B) consists in applying DrifNet on a real use case, exploring the ability of the proposed method to generate reliable trajectories from Ocean Reanalysis Model velocity fields. For this task, we build a database of real drifters trajectories (from Copernicus Marine Service (CMEMS)), considered as ground-truth. In this experiment, DrifNet is fed with velocity fields from Ocean Reanalysis Model GLORYS12 and trained to reproduce the ground-truth drifters trajectories.

For both experiments (A) and (B), we also assess the robustness of the method based on the following Lagrangian metrics: Last time step mean separation distance (Mean D), the ensemble average of Liu index score between ground truth and simulated trajectories and mean absolute error between Lagrangian time scales (ΔT) of ground-truth and simulated trajectories respectively. The comparative analysis between the proposed method, the numerical advection tool model (Ocean Parcels) and state-of-the-art learning-based methods (CNN and LSTM) puts in evidence the robustness of DrifNet when simulating realistic trajectories and it’s efficacy in outperforming existing methodologies, see Table 1.

Table 1: Performances metrics for Lagrangian drift reconstruction benchmark comparison between proposed method DrifNet and state of the art models. For the experiment (A) all the models are conditioned with U and V velocities from partially-observed OSSE fields and the Sea Surface Height (SSH) is obtained from the fully-known Nature Run field. For the experiment (B) all the models are conditioned with U and V velocities from reanalysis GLORYS12 fields and the Sea Surface Height (SSH) is obtained from satellite observation data from L4 product based on optimal interpolation.

Experiment	Method	Mean D (km)	Mean Liu index	ΔT (days)
(A)	Ocean Parcels (U, V)	53.6	0.87	0.1
	DrifNet (U, V)	45.4	0.71	1.96
	CNN (U, V)	51.7	0.73	2.22
	LSTM (U, V)	47.9	0.69	4.45
	DrifNet (U, V, SSH)	23.5	0.31	1.12
(B)	Ocean Parcels (U, V)	74.5	0.65	2.2
	DrifNet (U, V)	63.9	0.53	0.05
	CNN (U, V)	66.6	0.57	0.31
	LSTM (U, V)	64.1	0.55	2.1
	DrifNet (U, V, SSH)	60	0.52	0.33

We also explore how DrifNet adapts to different input conditions. Significantly, the inclusion of the observed Sea Surface Height (SSH) from fully-controlled framework for experiment (A) and the L4 SSH product for the experiment (B), both containing the geostrophic component of the current missing in the modeled currents, allows to increase the accuracy of the simulated Lagrangian trajectories in both (A) and (B) experiments along the evaluation metrics, see Table 1. In the comparative analysis against state-of-the-art learning-based and model-based approaches, the proposed method consistently demonstrated a better performance along chosen Lagrangian metrics. The virtual framework allowed for a controlled environment to objectively assess the method’s capabilities, highlighting its efficacy in outperforming existing methodologies. From the other hand, DrifNet not only worked well for making virtual trajectories but also did a good job with real drifter trajectories. Finally, we highlight the adaptability of DrifNet to various types of input fields We prove the ability of the model to correctly retrieve larger-scale dynamics from additional SSH fields. DrifNet also successfully combines various inputs in order to produce reliable trajectories and outperform state-of-the-art model-based and learning-based methods.

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