Predicting Ocean Currents for Robot Navigation

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Introduction

Operating autonomous vehicles in expansive marine environments is challenging. Oftentimes the disturbances from ocean currents are much greater than a vehicle's total control authority. In these scenarios, it is imperative that marine robots make *accurate* predictions of current disturbances in order to budget their energy consumption efficiently. For a robot, however, this can be a daunting task; because in most coastal regions, current disturbances arise from many complex phenomena, which are difficult to model effectively. Past applications of robots to these domains have incorporated current data from high-fidelity, ocean-water simulators using Gaussian processes. **Here we investigate a method to improve upon prior applications of Gaussian processes by incorporating more relevant temporal information.**

Conclusion

The predictive accuracy of Gaussian processes can be improved by structuring training sets with time traces, rather than entirely with independent random samples. Our preliminary results show that introducing a higher degree of temporal correlation promotes better emulation of the complex oscillations ocean currents exhibit.

Statistical measures of correlation indicate that model outputs are significantly dependent upon each other. We expect that further improvements to the prediction of ocean currents can be obtained by considering the cross correlation of model outputs. There are two promising avenues to obtain better predictions:

1. Linear Models of Coregionalization: Instantaneous output mixing with linear combinations
2. Convolutional Models: Consider output mixing over finite time scales.

References

[1] G. Hollinger, A. Pereira, J. Binney, T. Somers, and G. Sukhatme. Learning uncertainty in ocean current predictions for safe and reliable navigation of underwater vehicles. *Journal of Field Robotics*, 33(1):47–66, 2016.

[2] C. Rasmussen and C. Williams. *Gaussian Processes for Machine Learning (Adaptive Computation and Machine Learning)*. The MIT Press, 2005.

[3] D. Kruger, R. Stolkin, A. Blum, and J. Briganti. Optimal auv path planning for extended missions in complex, fast-flowing estuarine environments. In *Proceedings 2007 IEEE International Conference on Robotics and Automation*, pages 4265–4270, April 2007.

[4] T. Koay and M. Chitre. Energy-efficient path planning for fully propelled auvs in congested coastal waters. In *2013 MTS/IEEE OCEANS - Bergen*, pages 1–9, June 2013.

Methods

Relating Data Samples: A squared-exponential kernel function κ is used to measure similarity between samples. As in previous applications [1], spatiotemporal locality attributes similarity through a sum of squared differences, and a sinusoidal term expresses periodic similarity:

$$\kappa(\mathbf{x}, \mathbf{x}') = \alpha^2 \exp\left[\frac{1}{\ell_T^2}\sin^2\left(\frac{\pi}{T}|t - t'|\right) + \sum_{j=1}^{3}\frac{(x_j - x_j')^2}{\ell_j^2}\right]. \tag{1}$$

Predicting Current: Given a data set $\mathcal{D} = \{(\mathbf{x}, y)\}_{1:N}$, where $\mathbf{x}_i = (\text{lat, long , time})$, and y takes on horizontal or vertical current speed, we use Gaussian processes to predict ocean currents:

$$v_* = \mathbf{K}_*(\mathbf{K} - \sigma^2\mathbf{I})^{-1}\mathbf{y}, \qquad \Sigma_* = \mathbf{K}_{**} + \sigma^2\mathbf{I} - \mathbf{K}_*^\top(\mathbf{K} + \sigma^2\mathbf{I})^{-1}\mathbf{K}_*. \tag{2}$$

Temporal Correlation: Temporal variations in current signals are better captured if $\mathcal{D}$ contains temporally-correlated sequences. Let $\tau = (\mathbf{x}_{1:T}, y_{1:T})$ be the time trace of labeled examples of some lat-long position. We predict ocean current with the training set

$$\mathcal{D}_{\text{corr}} = \{\tau_j \mid \tau_j = (\mathbf{x}_{1:T}, y_{1:T})_j,\ \forall\ j = \text{lat-long pairs}\}. \tag{3}$$

Computing Energy: Current predictions are used to estimate the energy required for propulsion. Energy is a function of ground velocity $\mathbf{v}_g = \mathbf{v}_t + \mathbf{v}_c$, where $\mathbf{v}_t$ is the velocity which the vehicle requires to steer.

$$v_t = \underset{v \in [v_t^{\min}, v_t^{\max}]}{\arg\min}\ v\hat{\mathbf{v}}_g - \mathbf{v}_c, \qquad E(x_i, x_j), = \alpha v_g^2 \mathtt{d}(x_i, x_j). \tag{4}$$

Computing Trajectories: Current predictions contribute to energy estimates, which are subsequently used in a planning algorithm to compute robot trajectories. We use the Probabilistic Roadmap algorithm to generate a graph of candidate trajectories, then search the graph with A* to return the minimum-energy path.

Results

Our experiments investigate the efficacy of training Gaussian processes using a temporally-correlated dataset $\mathcal{D}_{\text{corr}}$. Previous instantiations of Gaussian Processes used to predict ocean currents are based upon pure i.i.d. datasets $\mathcal{D}_{\text{i.i.d}}$. Elements of both datasets are obtained from nearest neighbor results with respect to lat-long and time. Labels $y \in \{u, v\}$ are obtained from the NYHOPS current model.

Time Trace Comparisons: We selected a random pair of lat-long coordinates from the New York City coastal region then predicted current magnitude over a forty-eight hour period. Predictions using a temporally-correlated dataset seem to model current variations more closely than a purely i.i.d. dataset.

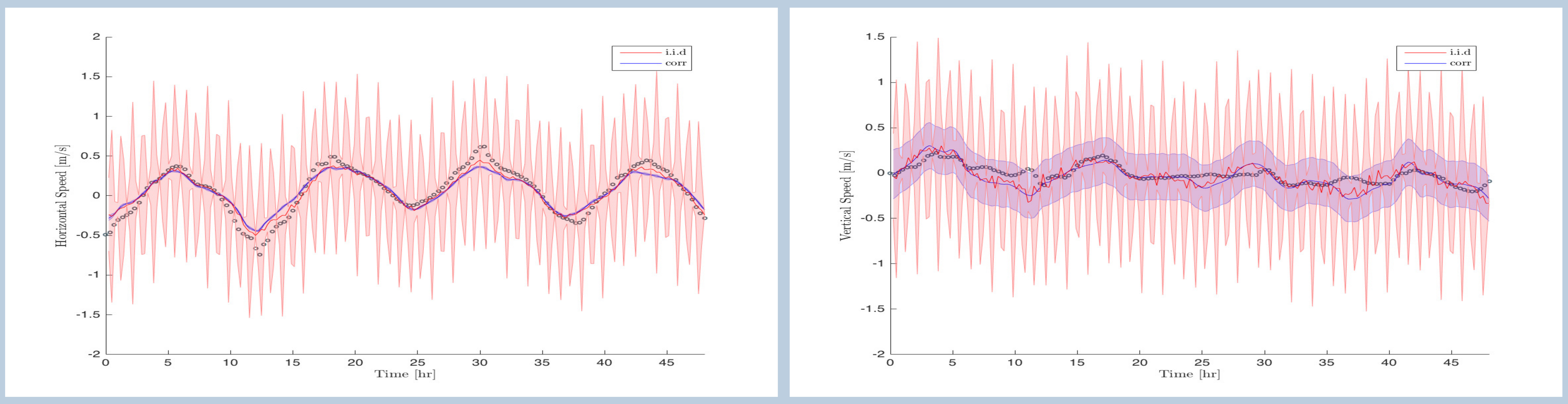

Figure 1: Time traces of current speed components: i.i.d. data (red), temporally-correlated data (blue)

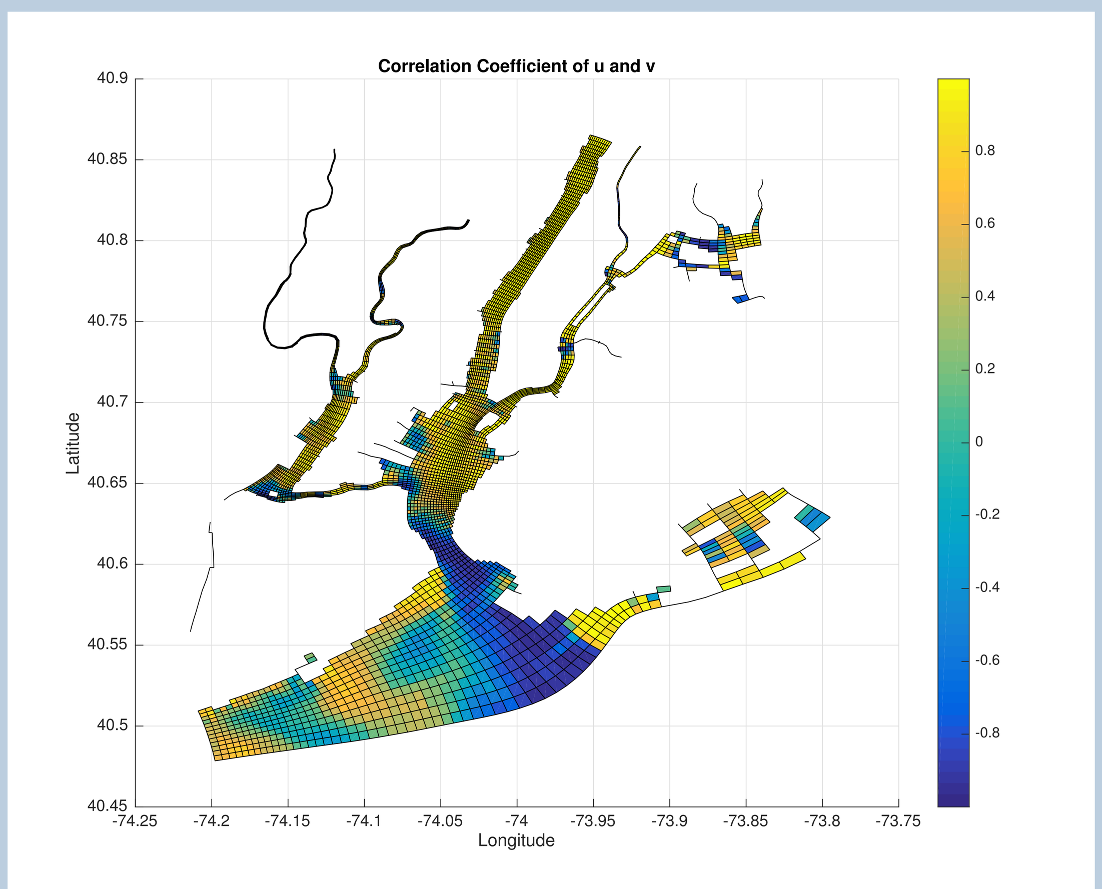

Figure 2: Correlation intensity of current

	Horizontal Speed	Vertical Speed
$\mathcal{D}_{\text{i.i.d}}$	13.1	3.1
$\mathcal{D}_{\text{corr}}$	11.5	2.9

Table 1: Mean Squared Error with same parameters

Output Correlations: A naive application of Gaussian processes to model multiple outputs requires independence between the outputs. Our preliminary analysis indicates, however, strong correlation between horizontal and vertical current exists. This suggests that further improvements could be made to predictive models by considering such correlations.