Reduced Order Modeling for Stochastic Prediction and Data Assimilation Onboard Autonomous Platforms At Sea

by

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Abstract

There are many significant challenges for unmanned autonomous platforms at sea including predicting the likely scenarios for the ocean environment, quantifying regional uncertainties, and updating forecasts of the evolving dynamics using their observations. Due to the operational constraints such as onboard power, memory, bandwidth, and space limitations, efficient adaptive reduced order models (ROMs) are needed for onboard predictions. In the first part, several reduced order modeling schemes for regional ocean forecasting onboard autonomous platforms at sea are described, investigated, and evaluated. We find that Dynamic Mode Decomposition (DMD), a data-driven dimensionality reduction algorithm, can be used for accurate predictions for short periods in ocean environments. We evaluate DMD methods for ocean PE simulations by comparing and testing several schemes including domain splitting, adjusting training size, and utilizing 3D inputs. Three new approaches that combine uncertainty with DMD are also investigated and found to produce practical and accurate results, especially if we employ either an ensemble of DMD forecasts or the DMD of an ensemble of forecasts. We also demonstrate some results from projecting / compressing high-fidelity forecasts using schemes such as POD projection and K-SVD for sparse representation due to showing promise for distributing forecasts efficiently to remote vehicles. In the second part, we combine DMD methods with the GMM-DO filter to produce DMD forecasts with Bayesian data assimilation that can quickly and efficiently be computed onboard an autonomous platform. We compare the accuracy of our results to traditional DMD forecasts and DMD with Ensemble Kalman Filter (EnKF) forecast results and show that in Root Mean Square Error (RMSE) sense as well as error field sense, that the DMD with GMM-DO errors are smaller and the errors grow slower in time than the other mentioned schemes. We also showcase the DMD of the ensemble method with GMM-DO. We conclude that due to its accurate and computationally efficient results, it could be readily applied onboard autonomous platforms. Overall, our contributions developed and integrated stochastic DMD forecasts and efficient Bayesian GMM-DO updates of the DMD state and parameters, learning from the limited gappy observation data sets.

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