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AN IMPROVED DEEPONET FRAMEWORK TO REDUCE COMPUTATIONAL DEMAND IN PREDICTOR-CORRECTOR GUIDANCE

Abstract

Predictor-corrector guidance is a promising technology that significantly enhances the accuracy of atmospheric entry processes and is anticipated to be applied in the next generation of high-precision atmospheric planetary landing missions, such as manned Mars landings and cargo delivery missions. However, this guidance mode requires the prediction of the probe's future state and the correction of guidance commands, where the prediction link demands extensive iterative calculations, severely limiting the method's practical application. The recently proposed Deep Operator Networks (DeepONet) offer a novel approach by utilizing compact neural networks to replace traditional integral operators, thus bypassing the iterative integration steps. This study proposes an improved DeepONet-based framework tailored to the Predictor-corrector guidance needs, aiming to directly determine the probe's state, thereby replacing the iterative calculation prediction part in the correction guidance algorithm. Compared to the original DeepONet, this enhanced framework incorporates initial conditions and model parameters as inputs, in addition to control configuration profiles and prediction moments, to meet the guidance task's requirements. The framework can accurately infer the probe's state in milliseconds. Moreover, by incorporating the concept of Physics-Informed Neural Networks (PINN), the training scheme integrates physical information, simplifying the training data organization and enhancing the model's extrapolation capability. Unlike previous attempts to simplify probe dynamics for faster prediction, our approach offers a high-fidelity digital twin paradigm, ensuring the adaptation to all critical variables in actual engineering tasks simultaneously. This notable development paves the way for future research to enhance guidance algorithms, overcome computational barriers, and promote the practical implementation of Predictor-corrector guidance systems in aerospace engineering.