Flow State Estimation and Optimal Control for Autonomous Underwater Docking

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The capabilities of marine vehicles, such as autonomous underwater vehicles (AUVs) and remotely-operated vehicles (ROVs), have significantly advanced to perform complicated operations such as navigating through unexplored and dynamic environments, inspection of underwater structures, and monitoring of ocean conditions in deep waters. However, the limited energy resources of AUVs and tethered connectivity of ROVs constrain survey lengths and subsequently increase the operational costs. Underwater docking stations that can recharge vehicles and transmit their data offer a potential solution to extend the endurance of vehicles. In this work, we consider the docking station to be powered through a floating wave energy converter (WEC), thereby enabling on-site energy harvesting and power transfer. As a main contribution, we present a navigation framework that couples flow state estimation with model predictive control (MPC) to perform autonomous underwater docking with a WEC under various ocean conditions.

I. Flow State Estimation

Unknown background flow can cause perturbations to an underwater vehicle's motion, leading to an unsuccessful attempt at docking. Prior works have utilised data from acoustic positioning devices and acoustic Doppler current profilers (ADCPs) to estimate the flow velocity. However, the use of ADCPs significantly increases the costs. In this paper, we adapt the approach presented in [1], which considers the coupling between vehicle motion and ocean currents to facilitate flow state estimation, for reliable docking with fewer failures.

Uniform complete observability of the flow state, along the vehicle trajectory, is maintained by obtaining optimal control input that minimizes the maximum variance of the flow state estimation. To facilitate this, $\mathcal{F}$ is defined as the information metric, that corresponds to the observability and performance of the flow state estimation, and can be described as

$$\mathcal{F} = \lambda_{min}(\mathcal{G}_{cg}^{\nu_{c1}}(-\infty, k+1)) \tag{1}$$

where $\nu_{c1} \in \mathbb{R}^3$ represents the linear component of the flow velocity, $\lambda_{min}(.)$ denotes the smallest eigenvalue of (.) and $\mathcal{G}_{cg}^{\nu_{c1}}$ represents the constructability gramian of the linearly time-varying ocean flow system.

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II. Optimal Control Problem

Extending our previous work [2], this article presents a navigation framework that incorporates flow state estimation into the MPC formulation for a more reliable and robust docking approach. This is accomplished by modifying the objective function to include the information metric, defined in (1).

The discretized vehicle motion model can be defined as

$$\mathbf{x}(k+1) = f(\mathbf{x}(k), \mathbf{u}(k)), \tag{2}$$

where $\mathbf{x} \in \mathbb{R}^{12}$ represents the vehicle state vector, $\mathbf{u} \in \mathbb{R}^6$ is the control input and f represents the discretized vehicle motion.

At time $k = t$, the optimal control problem seeks to find a sequence of optimal control inputs $\mathbf{U}^\star = \{\mathbf{u}^\star(0), \cdots, \mathbf{u}^\star(N)\}$ by minimizing the objective function J such that

$$\begin{aligned}\mathbf{U}^\star = \underset{\{\mathbf{u}(0),\cdots,\mathbf{u}(N)\}}{\operatorname{argmin}} \; J = \sum_{k=t}^{t+N-1} \Big[\| \mathbf{x}(k) - \mathbf{x}_W(k) \|_Q^2 \\ + \| \mathbf{u}(k+1) - \mathbf{u}(k) \|_R^2 - \lambda_{min}(\mathcal{G}_{cg}^{\nu_{c1}}(-\infty, k+1)) \Big] \\ + \| \mathbf{x}(N) - \mathbf{x}_W(N) \|_P^2 \end{aligned} \tag{3}$$

$$\text{subject to (2)},\ \mathbf{x}(0) = \mathbf{x}_0,\ \mathbf{x}_{min} \leq \mathbf{x}(k) \leq \mathbf{x}_{max},$$
$$\mathbf{u}_{min} \leq \mathbf{u}(k) \leq \mathbf{u}_{max},$$

where $\mathbf{x}_W \in \mathbb{R}^6$ represents the WEC state vector, N is the prediction horizon, and P, Q, and R are weight matrices.

The key significance of the proposed approach is that it enables the vehicle to counter the influence of unknown flow disturbances while simultaneously moving closer to the docking station, in an optimal manner.

III. Results and Discussion

Initial results demonstrate the vehicle successfully approaching the docking station while countering the influence of ocean currents along its path. Additionally, we reformulated the problem in a sequential manner and validated its performance under various ocean conditions. Furthermore, we are also explicitly modeling the dynamics of different types of WECs. Future work includes conducting field trials on a real robot and extending this concept to support wave-current interactions.

References

[1] D. Chang, M. Johnson-Roberson, and J. Sun, "An active perception framework for autonomous underwater vehicle navigation under sensor constraints," *IEEE Transactions on Control Systems Technology*, 2022.

[2] R. Vivekanandan, D. Chang, and G. A. Hollinger, "Model predictive control for underwater vehicle rendezvous and docking with a wave energy converter," *Proc. IEEE International Conf. on Robotics and Automation Workshop on Reliable AI for Marine Robotics: Challenges and Opportunities*, 2021.