Power-Aware Inverse-Search Machine Learning for Low Resource Multi-Objective Unmanned Underwater Vehicle Control (Student Abstract)

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Abstract

Flapping-fin unmanned underwater vehicle (UUV) propulsion systems enable high maneuverability for tasks ranging from station-keeping to surveillance but are often constrained by their limited computational power and battery capacity. Previous research has demonstrated that time-series neural network models can accurately predict the thrust and power of certain fin kinematics based on the specified gait coupled with the fin configuration, but can not fit an inverse neural network that takes a thrust request and tunes the kinematics by weighting thrust generation, smooth movement transitions, and power attributes. We study various combinations of the three weights and fin materials to create different 'modes' of movement for a multi-objective UUV, based on controller intent using an inverse neural network. Finally, we implement and validate an enhanced power-aware inverse model by benchmarking on the Raspberry Pi Model 4B system and testing through generated simulated movements.

Introduction

Unmanned underwater vehicles (UUVs) have a variety of applications including minesweeping, search and detection operations, and bathymetric mapping, among others. While traditional propeller-based UUVs operate well in deep water environments, bio-inspired fins offer greater agility and maneuverability necessary for near-shore operations. Additionally, studies have demonstrated that animals swim at an optimal Strouhal number for power efficiency (Taylor, Nudds, and Thomas 2003; Rohr and Fish 2004; Masud, La Mantia, and Dabnichki 2022), which flapping fins can replicate for high maneuverability at low speeds (Blake 1979; Fish 2013).

To achieve this desired high maneuverability and efficiency at low speeds, a control system needs to make quick adjustments at each movement to guarantee the performance of the UUV in a practical setting. The solution, an inverse-search method, is typically difficult to implement on aerial and underwater control systems (Zhou, Gómez-Hernández, and Li 2012; Hansen and Cordua 2017), because it often requires searches that will invoke a forward model multiple times. While this is usually too computationally intensive for real-time control, we previously successfully developed an inverse model for UUVs, since they have a more flexible time constraint compared to other aerial and underwater control systems (Lee et al. 2023). This inverse search model is able to optimize for two cycle-by-cycle performance metrics: thrust generation and smoothness of transitioning kinematics. However, it fails to capitalize on the benefits of efficiency and minimizing power consumption that bioinspired flapping fin designs offer (Zhou et al. 2023). Therefore, we enhance our inverse model by making it power-aware.

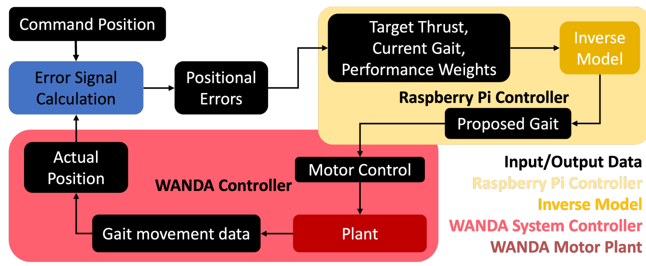

Figure 1: An integrated inverse model on the control system

Previous studies have explored the effects that varying material, flexibility, and shape alongside kinematic inputs have on a flapping fin's thrust output and power efficiency to better replicate and understand fish hydrodynamics (Lauder and Madden 2006; Tangorra et al. 2007; Nedelcu et al. 2018; Mignano et al. 2019; Sampath et al. 2020). Various approaches including high-fidelity computational fluid dynamics (CFD) simulations (Palmisano et al. 2013) and using machine learning to develop surrogate models (Viswanath et al. 2019; Lee et al. 2021) have provided the ability to predict a certain thrust output or power consumed from a single gait, but can not pair knowledge together to understand all possible gaits (Bi et al. 2014; Shan, Bayiz, and Cheng 2019).

In this work, we demonstrate that a search-based (Torczon 1997) inverse model optimizing thrust, kinematics smoothness, and power consumption is able to both meet benchmarked time constraints while significantly improving the efficiency of cycle-by-cycle adjustments without high trade-off of thrust generation, analyzing various combinations of weights to determine optimizations for various missions.

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Materials and Methods

Displayed in Figure 1, the inverse model operates each cycle based on three inputs from the PID controller (Geder et al. 2008): desired thrust, current gait, and optimization weights to output a proposed gait. This proposed gait is fed into the motor, which will switch to the new gait after one cycle. The cycle repeats, where an error signal calculation updates the actual position to find the next request for the inverse model.

A gait combination is defined by the stroke (Φ) and pitch (Θ) of a movement, alongside the flapping frequency and stroke-pitch offset. The range of gaits is constrained to parameter values that are physically achievable given a frequency, as defined in Equation 1. At higher frequencies, the fins are physically unable to reach certain amplitudes.

$$\text{Attainable gaits:} \begin{cases} 0 < \Phi < 97 - f * 30 \\ 0 < \Theta < 75 - f * 26 \end{cases} \tag{1}$$

There are 864 unique gaits spanning this range. This data is fed into a forward Long Short Term Memory (LSTM) model able to input a gait and predict either the thrust generated or the power consumed. The rigid fin model has an error of 0.0002 N and 0.0236 W, PDMS 1:10 of 0.0186 N and 0.0720 W, and PDMS 1:20 of 0.0041 N and 0.0268 W.

In selecting a desired set of fin kinematics, preference is given to high thrust, low power, and smooth kinematics using weights that sum to one: $w_T + w_P + w_K = 1$. w_T is the weight on thrust, w_P is the weight on power, and w_K is the weight on kinematics smoothness.

Experimental Results

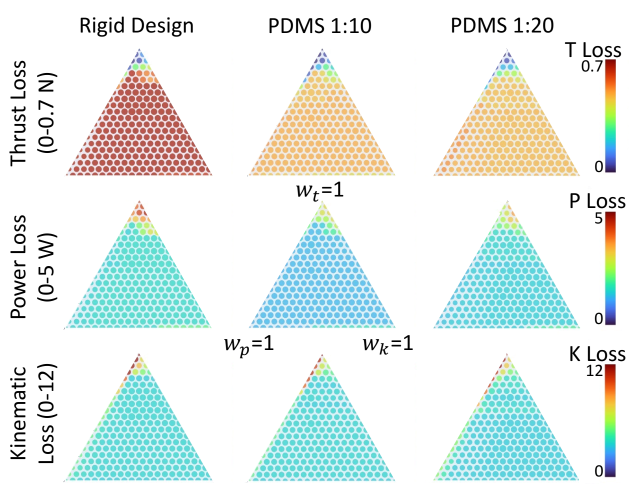

Figure 2: Analysis of different weight combinations. Red indicates high loss, blue indicates minimized loss. Max triangle weights is thrust: top, power: left, and kinematics: right.

Adding power opens new possibilities for different combinations of weights, with varying effects on the thrust and power loss. To test the effectiveness of our power-aware model, we develop a series of tests that test all possible combinations of the three weights (w_T, w_P, w_K). To try to discover an optimal weight combination, we run a standard set of thrust requests with varying differences between the starting thrust and desired thrust, and repeat this for all combinations of weights with a 0.05 difference.

Average thrust, power and smoothness losses for each weight combination are shown for the all three fin types demarcated by column in Figure 2. These results demonstrate that power loss and smoothness loss behave similarly, as switching between extremely different movements results in a higher power consumption. A significant trade off between thrust exists; thrust loss is minimized to around 0.2 N when weighted 0.8 or higher, but rapidly escalates to around 0.5 N average loss when below 0.8. For all three fins, the lowest thrust loss is achieved at (1, 0, 0), but a combination around (0.8, 0.2, 0) can improve the average power loss by a factor of 3 W with only a 0.1 N trade off in thrust. These performances are important; the full ranges of thrust and power profiles are 0-1.67 N and 0-7.9 W, indicating that these optimizations significantly improves the overall power efficiency of any suggested movement.

Notably, while all three designs have similar kinematic smoothness profiles across all possible weight combinations, the flexible PDMS 1:10 and PDMS 1:20 have significantly lower thrust losses averaging around 0.5N, indicating that a flexible polymer loses less thrust generation when optimizing for power and kinematic metrics than the rigid fin. Additionally, the 1:10 design performs better in minimizing power loss than either fin, averaging around 1.2W compared to 1.5W. Thus, the 1:10 design is most effective in minimizing power loss with a low thrust tradeoff.

Our new model that includes the forward LSTM power model creates additional computational power draw and time to calculate a gait. Additionally, we're able to change the size of the model to adjust for different frequencies or speeds. With our optimal weight setting, we can validate that the new model is able to meet all time constraints with the prior model. Both the two constraint inverse model and the three constraint inverse model are benchmarked on the Raspberry Pi Model 4B-2GB, which is the device that runs the inverse model and communicates with the rest of the control system. The maximum time a calculation can take is 0.5s, as the maximum frequency of the flapping fin (2 Hz) would require a returned kinematic in under that time. Finally results will demonstrate the performance metrics for a generalized pattern search for all three fin designs, and allow us to conclude whether each inverse search model implementing power is or is not able to meet benchmarking standards while improving the loss from the prior model.

Conclusion

We test and develop optimal gait settings for rapid acceleration (high thrust), efficient movement (balanced weights), and low-energy stationkeeping for various underwater control settings. In the future, we plan to finalize benchmarking of the inverse model, and to validate our work by testing the time performance of the inverse control model while measuring the improvements in thrust generation and power efficiency the inverse control model is able to achieve. This will be done with a series of set gaits and movements on the finished physical control system.

Acknowledgements

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