# OPTIMIZING ROBOTIC AQUATIC LOCOMOTION 

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Optimizing Robotic Aquatic Locomotion
Abstract of tentative senior thesis at Barry University. Thesis supervised by Professor Mysore S. Jagadish.

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Carangiform (tuna-like) swimming is effective in producing forward thrust through counterrotating vortices left in the wake. B. Ahlborn et al. (1997) mimicked carangiform motions with a computer-controlled fishtail simulation apparatus. Ahlborn et al. states two claims: (i) fish hide their "footprints" through the destruction of these vortices, which increases efficiency and (ii) thrust force of his vortex-producing robot is derived by $\mathrm{F}_{\mathrm{x}}=(2 / \pi) \mathrm{K} \rho \mathrm{hA}^{3} \mathrm{f}^{2}$. K is a water entrainment constant of $40, \rho$ is the density of water, $h$ is the submerged height of the tailfin, $A$ is the deflection amplitude, and f is the frequency. While the peduncle's deflection amplitude was held constant, we swam our carangiform-swimming robot using 160 unique motions (gaits) to obtain values of efficiency and velocity at four distinct frequencies, ten distinct phase angles, and four distinct tailfin amplitudes. Maximum values of efficiency and velocity were found on 3-D surfaces. Our experimental thrust force was estimated by creating a function of drag forces at different steady-state velocities. When using Ahlborn et al.'s equation, our thrust force appeared to be proportional to a square root function of the frequency. Under certain constraints, we determined optimal thrust and efficiency, which yields the best gait at 40P80W20. Understanding these relationships allows us to control and predict the efficiency, velocity, and thrust force of our robot within certain parameters.

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## Chapter 1, Introduction

Fish are excellent, efficient swimmers. By adding momentum to the water and shedding counter-rotating vortices in the wake, a swimming fish can produce forward thrust through undulating motions of its body and/or tail (Ahlborn et al. 1997, Muller et al. 1997). Five of the various locomotion modes are anguilliform (eel-like), sub-carangiform (i.e. trout), carangiform (i.e. mullet), thunniform (i.e. bluefin tuna), and ostraciiform (oscillatory).

For several decades, mechanical engineers have attempted to reproduce the motions of this animal with robots. These scientists have attempted to mechanically replicate the relative quietness, high maneuverability, high adaptability, and high efficiency that fish have demonstrated for many years. Since there is no handbook on building such robots, many of the ideas are innovative and creative. For instance, the Charles Stark Draper Laboratory and the Massachusetts Institute of Technology (MIT) have engineered robots to swim like fish. Draper Laboratory created the Vorticity Control Unmanned Underwater Vehicle (VCUUV); MIT produced RoboTuna. Both robots attempt free-swimming.

One of the main difficulties in doing this successfully is that fish are very complex. For a free-swimming fish, the degrees of freedom are found in the pitch, roll, spin, lateral, longitudinal, and vertical displacements. This does not take into account the many other degrees created along the body, like bending and twisting. Therefore, engineers have had to make innovative robots and use mathematical models to get the best performance from their designs. The use of mathematics has been an essential tool to these pioneers.

At the California Institute of Technology, we studied issues in fluid mechanics, nonlinear control, and sensing that are necessary for the development of a self-propelled robot. In our
laboratory, our robot "fish" could swim in both carangiform and thunniform swimming modes. Finding optimal motions at the different levels of efficiency, velocity, and thrust provides an understanding of the performance and control of the robot. For a given gait input, we should be able to predict the values of velocity, efficiency, and thrust forces.

Multiobjective Optimization (MO), also known as multicriteria and vector optimization, can be used to find the best tradeoff of values between two interdependent objects. Usually, improvement in one object's value would cause the other object to lose value, and vice versa. In our case, we wanted to find the "best" gait by optimizing the thrust and efficiency ratio for our robot.

## Chapter 2, Background Information

Various studies, from such fields as biology, mathematics, and engineering, are useful in studying how fish swim, naturally and mechanically. Marine biologists have studied vortex shedding in the wake and the interaction between the water and the fish body (Muller et al. 1997). They have approximated the motion of a mullet to be sinusoidal (Muller et al. 1997). M. J. Lighthill (1970) offers a preliminary quantitative analysis of how a series of modifications to that basic undulatory mode, found in vertebrates (and especially fish), tends to improve speed and hydromechanical efficiency. He states that the carangiform mode is advantageous from the point of view of propulsive efficiency. Ahlborn et al. (1997) claimed that fish hide their "footprints" through the destruction of these vortices, which increases efficiency. Carangiform locomotion is evident when the final third to half of the body is undulating while the remainder is fairly rigid. Carangiform-like swimming is effective in creating counter-rotating vortices, whirling masses of water within a limited area (Fig. 1).


Fig. 1. Thrust production in the wake.

The equation for thrust force based on experiments with a vortex-shedding apparatus (Ahlborn et al. 1990, Ahlborn et al. 1997) follows:

$$
\begin{equation*}
\mathrm{F}_{\mathrm{x}}=\frac{2}{\pi} \mathrm{~K} \rho \mathrm{hA}^{3} \mathrm{f}^{2} \tag{1}
\end{equation*}
$$

Ahlborn et al. computer-controlled apparatus has a tail that moves in premeditated paths and focused mainly on half-flips. It created a vortex with the first tail flip (Ahlborn et al. 1997). Then inverted the vortex on the return stroke (Ahlborn et al. 1997). Equation one describes the thrust force produced along the direction of motion. Shapiro (1961) used drag experiments as a vehicle for discussing the fundamentals of fluid dynamics.

Mathematicians used optimization for various applications. According to Eschenauer et al. (1986), Gottfried W. Leibniz and Leonhard Euler used infinitesimal calculus to find the extreme values of functions. This made it possible for pioneers to study various new fields of mechanics (Eschenauer et al. 1986). For example, Bernoulli and D. Bernoulli used optimization on isoperimetric problems; Isaac Newton used the method for minimizing the resistance of a revolving body (Eschenauer et al. 1986). Vilfredo Pareto initially used MO in economics (Eschenauer et al. 1986). Using this technique can aid us in our understanding of underwater locomotion and control of our robot's performance.

## Chapter 3, Materials and Methods

The experiments were performed by swimming a computer-controlled robot, which is supported by a carriage that rolled on a pair of frictionless rails that ran parallel along the top of the aquarium (Fig. 2a). This carriage held the twin motors with motor encoders, transmission, and a Polhemus 3 -space motion sensor. The Polhemus motion sensor is in a fixed position. The Polhemus 3-D detector receives and records the three-dimensional position of the sensor over time. The design specifications of the robot can be obtained on request.


Fig. 2. (a) Side and (b) top view of robot.

To mimic carangiform motion, the three-link robot used the final third of its body to move while the rest of the body was fairly rigid. This third had two main parts called the peduncle and tailfin, which both turned independently about its respective joint in a sinusoidal manner (Fig. 3). The robot was designed to propel itself by two joint degrees of freedom for the peduncle and the tailfin. Additionally, it had one to three degrees of freedom for lateral, longitudinal and rotational motions within the plane of the water surface (Fig. 2b). For our experiment, motions were limited to three degrees of freedom at the turning at the two joints and
the forward motion. Motors encoders measure the actual angles created by each motor. These values are stored in matrices, joutp and joutt. Based on the difference between desired and actual $\theta$ values, the computer increased or decreased power sent to the motor(s).


## Fig. 3. (a) Side and (b) top view of three-link robotic carangiform locomotion.

The peduncle and tailfin move as a sinusoidal function of time (Fig. 4). Both joint angles, $\theta_{1}$ and $\theta_{2}---$ in obvious notation, $\theta_{\mathrm{p}}$ and $\theta_{\mathrm{t}}---$ are independent of each other (see Fig. 3). We have joint angles represented such that

$$
\begin{equation*}
\theta_{p}=\left(\omega t+\phi_{p}\right) \tag{2}
\end{equation*}
$$

and

$$
\begin{equation*}
\theta_{\mathrm{t}}=\left(\omega t+\phi_{\mathrm{t}}\right) \tag{3}
\end{equation*}
$$

However, we let

$$
\begin{equation*}
\theta_{p}=\omega \mathrm{t} \tag{4}
\end{equation*}
$$

and

$$
\begin{equation*}
\theta_{\mathrm{t}}=\omega_{\mathrm{t}}+\phi \tag{5}
\end{equation*}
$$

with

$$
\begin{equation*}
\phi=\left(\phi_{\mathrm{t}}+\phi_{p}\right), \tag{6}
\end{equation*}
$$

for a single phase-difference variable. The amplitudes, $A_{p}$ and $A_{t}$, were measured in encoder ticks, where $90^{\circ}$ deflection is equivalent to 512 encoder ticks. We created unique gaits by inputting a text file with the desired parameters and using equations that follows:

$$
\begin{equation*}
\mathrm{j}_{\mathrm{p}}=\mathrm{A}_{\mathrm{p}} \sin (\omega \mathrm{t}) \tag{7}
\end{equation*}
$$

$$
\begin{equation*}
\mathrm{j}_{\mathrm{t}}=\mathrm{A}_{\mathrm{t}} \sin (\omega \mathrm{t}+\phi) . \tag{8}
\end{equation*}
$$

Text files were inputted as gait names that were represented by two digits for the phase angle, followed by a "P", the frequency in tenths of radians per second, followed by a "W" for $" \omega, "$ one digit for the amplitude of the peduncle, and one digit for the amplitude of the tailfin. For example, "40P20W23" commanded the robot to swim at a frequency of 2.0 radians per second with the peduncle amplitude at 2 in hundreds of encoder ticks, and the tailfin at 3 in hundreds of encoder ticks (Fig. 4).


Fig. 4. Sinusoidal motion of tailfin and peduncle for 40-degree phase difference, frequency of $2.0 \mathrm{rad} / \mathrm{s}$, peduncle's amplitude at 200 encoder ticks, and tailfin amplitude at 300 encoder ticks.

We used our desired parameters to create a unique gait name. After we entered a gait name, the robot "swam" while a Polhemus 3-D detector received and recorded the threedimensional position of the robot body over time. Data was obtained for 160 unique gaits for 4 distinct frequencies, 4 distinct amplitudes, and 10 distinct phase-difference angles. Values of
efficiency and velocity were derived. The frequencies were $2.0,4.0,6.0$, and 8.0 radians per second. The amplitude values were at $0,100,200$, and 300 encoder ticks. The phase-difference values were taken from $0^{\circ}$ to $90^{\circ}$ by increments of $10^{\circ}$.

## Optimizing velocity

Position was plotted at every fiftieth of a second (Fig. 5). Elapsed time per gait ranged from 12-15 seconds. Velocity was calculated by the distance traveled over the change of time, from 0.5 to 9.5 seconds. Three-dimensional surfaces of velocity were constructed for each of the frequencies (Fig. 6-9). These surfaces illustrated the relationship between different parameters of frequency, tailfin amplitude, and phase angle.


Fig. 5. Distance traveled over time.

Velocity Surface


Fig. 6. Frequency is $2.0 \mathrm{rad} / \mathrm{sec}$.


Fig. 7. Frequency is $4.0 \mathrm{rad} / \mathrm{sec}$.


Fig. 8. Frequency is $6.0 \mathrm{rad} / \mathrm{sec}$.


Fig. 9. Frequency is $8.0 \mathrm{rad} / \mathrm{sec}$.

## Optimizing efficiency

Relative efficiency is a function of velocity and the total power. It was calculated by dividing the total kinetic energy by the total power given to the motors during each run (Eqns. 911). The mass, m, of the entire robot was 34 kg (approx. 74.8 lbs ). We constructed 3-D surfaces of efficiency for each of the frequencies (Fig. 10-14).

$$
\begin{equation*}
\mathrm{KE}=\frac{1}{2} \mathrm{mv}^{2} \tag{9}
\end{equation*}
$$

$$
\begin{equation*}
\text { Total power }=\text { power }_{1}+\text { power }_{2} \tag{10}
\end{equation*}
$$

$$
\begin{equation*}
\text { Efficiency }=\frac{\mathrm{KE}}{(\text { Total power })} \tag{11}
\end{equation*}
$$



Fig. 10. Frequency is $2.0 \mathrm{rad} / \mathrm{sec}$.


Fig. 11. Frequency is $4.0 \mathrm{rad} / \mathrm{sec}$.


Fig. 12. Please, notice that the x and y -axes are switched from Fig. 11.

Relative Efficiency


Fig. 13. Frequency is $6.0 \mathrm{rad} / \mathrm{sec}$.


Fig. 14. Frequency is $8.0 \mathrm{rad} / \mathrm{sec}$.

## Controlling thrust

Equation 1 was analyzed. For the experimental thrust, K and $\rho$ remained as our constants. Frequency values were $2.0,4.0,6.0$, and 8.0 radians/second. Our submerged height, h, was 17.5 inches. Since A is the deflection amplitude of the tail tip, we converted our amplitudes values in MATLAB by using the equations that follows:

$$
\begin{equation*}
\mathrm{A}=\frac{|\mathrm{hmax}+\mathrm{hmin}|}{2} \tag{12}
\end{equation*}
$$

where

$$
\begin{equation*}
\operatorname{hmax}=\max \left(l \mathrm{lp} * \sin \left(\frac{\text { joutp } * 2 \pi}{2048}\right)+l t * \sin \left(\frac{\text { joutt } * 2 \pi}{2048}\right)\right) \tag{13}
\end{equation*}
$$

and

$$
\begin{equation*}
\operatorname{hmin}=\min \left(l \mathrm{lp} * \sin \left(\frac{\text { joutp } * 2 \pi}{2048}\right)+\mathrm{lt} * \sin \left(\frac{\text { joutt } * 2 \pi}{2048}\right)\right) \tag{14}
\end{equation*}
$$

The length of the peduncle, lp , was 0.127 m ( 5 inches); the length of the tailfin, lt, was 0.1651 m ( 6.5 inches). To find the experimental thrust force, we applied a constant force to the robot by tying a nylon string and tested different weights on a pulley system. As the robot moved in the forward direction, the drag force increased and acceleration decreased from its initial value of $9.8 \mathrm{~m} / \mathrm{s}^{2}$. It reached a steady-state velocity. At a steady-state velocity,

$$
\begin{equation*}
\text { Acceleration }=\frac{|\mathrm{T}-\mathrm{D}|}{\operatorname{mass}}=0, \tag{15}
\end{equation*}
$$

which lead to

$$
\begin{equation*}
|\mathrm{T}-\mathrm{D}|=0, \tag{16}
\end{equation*}
$$

demonstrating that the steady state drag is equal to the steady state thrust. We used the Polhemus to obtain a steady state velocity value for each weight (constant force). Using MATLAB, a thrust force versus velocity relationship was found using the linear and quadratic polyfit. For a constant acceleration, steady-state drag measurements were plotted against steady-state velocity values (Figs. 15-16).


Fig. 15. Experimental steady state drag measurements with quadratic polyfit curve.


Fig. 16. Linear and quadratic polyfit curves used to determine thrust force.

Using the linear and quadratic polyfit curves allowed us to input velocities of the corresponding gait names and acquire respective thrust values. By using these thrust values, we created experimental thrust surfaces (Figs. 17-18). In addition, we created a theoretical surface (Fig. 19) using Ahlborn et al.'s equation and the given parameters. Our experimental surface (Fig. 20) was then graphed on the same intervals as Fig. 19. Calculations were made within the programs, but the equations for our experimental thrust force can be found if needed.


Fig. 17. Surface of linear fit.

Quadratic


Fig. 18. Surface of Quadratic polyfit.


Fig. 19. Thrust predictions according to Ahlborn et al.


Fig. 20 Experimental thrust on the same axis.

## Optimizing gaits

We created constraints where the velocity and efficiency were nonnegative and of equal importance. We matched the range of relative efficiency to that of the velocity, added the corresponding values, and found the maxima in Microsoft Excel 2000.

## Chapter 4, Results

## Optimizing velocity

Maxima over the entire surface were found at the following gaits:
$-50 \mathrm{P} 20 \mathrm{~W} 22=0.4202 \mathrm{~meters} / \mathrm{sec}$
$-60 \mathrm{P} 40 \mathrm{~W} 21=0.8532 \mathrm{~meters} / \mathrm{sec}$
$-30 \mathrm{P} 60 \mathrm{~W} 22=1.0312$ meters $/ \mathrm{sec}$
$-40 \mathrm{P} 80 \mathrm{~W} 23=1.0440$ meters $/ \mathrm{sec}$

## Optimizing efficiency

Maxima over the entire surface were found at the following gaits:

$$
\begin{aligned}
& -80 \mathrm{P} 20 \mathrm{~W} 22=0.0056 \\
& -70 \mathrm{P} 40 \mathrm{~W} 21=0.0113 \\
& -50 \mathrm{P} 60 \mathrm{~W} 21=0.0139 \\
& -00 \mathrm{P} 80 \mathrm{~W} 20=0.0105
\end{aligned}
$$

## Controlling thrust

It appeared that our fish has

$$
\begin{equation*}
\mathrm{F}_{\mathrm{x}} \propto \mathrm{f}^{1 / 2} \tag{17}
\end{equation*}
$$

as opposed to

$$
\begin{equation*}
\mathrm{F}_{\mathrm{x}} \propto \mathrm{f}^{2} \tag{18}
\end{equation*}
$$

as stated by Ahlborn et. al. (Fig. 18-19). Our experimental thrust force seemed directly proportional to the square root of the frequency. Thrust force of the robot appeared less than expected, as well.

## Optimizing gaits

Where velocity and efficiency was of equal importance, the best motions were found at the following gaits:

The "best" gait was found at 40P60W21. It had a velocity of 0.9763 meters per second and an efficiency of 0.0139. The second, third, and fourth optimal gaits were at 30P60W21, 60P60W21, and 20P60W21, respectively (Tab. 1).

|  | tailfin amplitude (encoder ticks) |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 0 | 100 | 200 | 300 | $\underline{\text { MAX }}$ |
|  | 0 | $\mathrm{~N} / \mathrm{A}$ | $\mathrm{N} / \mathrm{A}$ | $\mathrm{N} / \mathrm{A}$ | $\mathrm{N} / \mathrm{A}$ | $\mathrm{N} / \mathrm{A}$ |
|  | 10 | 1.5986 | 1.3641 | 1.7148 | 1.6450 | 1.7148 |
|  | 20 | 1.6222 | 1.7515 | 1.5198 | 1.7037 | 1.7515 |
| phase | 30 | 1.5867 | 1.8494 | 1.5582 | 1.4022 | 1.8494 |
| difference | 40 | 1.6612 | 1.9363 | 1.3046 | 1.0889 | 1.9363 |
| (degrees) | 50 | 1.2537 | 1.7281 | 1.0794 | 1.0077 | 1.7281 |
|  | 60 | 1.4731 | 1.8082 | 1.1100 | 0.8670 | 1.8082 |
|  | 70 | 1.6113 | 1.7924 | 0.9491 | 0.6593 | 1.7924 |
|  | 80 | 1.5721 | 1.2510 | 0.7560 | 0.5145 | 1.5721 |
|  | 90 | 1.3679 | 1.5043 | 0.6931 | 0.5198 | 1.5043 |
|  | $\underline{\text { MAX }}$ | 1.6612 | 1.9363 | 1.7148 | 1.7037 | 1.9363 |

Table 1. Data used to find best gait; frequency at $6.0 \mathrm{rads} / \mathrm{sec}$

## Chapter 5, Discussion

## Optimizing velocity

We were interested in discovering the inputs that yield the fastest gait. Data shows that velocity increased as the frequency increases, while the amplitudes varied, and as phase angles seemed to decrease. Initially, we did see that relationship where velocity and frequency increased (Figs. 6-9). At increased frequencies, we got more distortion and irregularity, but the same relationships are consistent. It appeared that the amplitudes would vary for the different frequencies of velocity. Optimal velocity was achieved when phase angles were in the $30,40,50$, 60 values accompanied by high frequency and high amplitude. For future experiments, the 45 degree phase angle will be tested and analyzed. This may be the optimal phase angle according to previous unpublished work done with the older versions of the robot.

## Optimizing efficiency

We were interested in discovering the inputs that yield the most efficient gait within the restrictions. Data showed that efficiency increased as the frequency appeared to increase, the amplitude decreased, and the phase angle decreased. The relation between relative efficiency and frequency must be interpreted with caution. As frequency increased, the overall efficiency rose. But then in Fig. 14,overall efficiency dropped. Within the parameters, the efficiency was the best at a frequency of 6.0 radians $/ \mathrm{sec}$ (Figs. 10-14). Yet, there were huge drop-offs in the surfaces. We lost a lot of efficiency with a change of amplitude. Upon visual analysis, it appeared that would increase as frequency increased as long as the amplitude would decrease at the same time. We assumed that at high frequencies that the overall efficiency will decrease. The relationship with amplitudes here was difficult to interpret due to some randomness in the data. Changing the
phase angle varies the value for efficiency, almost unpredictably. Optimal efficiency may be found at a frequency at or near 6.0 radians $/ \mathrm{sec}$, with amplitude at or near 100 encoder ticks, and where phase angle is approaching 90 degrees.

With these results, we come closer to controlling the outputs that we want for a given gait. Efficiency and velocity differ where maxima were not found at the same gait. So by changing the parameters of the amplitude, frequency, and phase angle, we can achieve either optimal velocity or optimal efficiency. Further research will be done at different increased values of $A_{t}$ and $A_{p}$. Further experiments will be performed on the latest model.

## Controlling Thrust

Although we came to a different idea on thrust, our goal was not to disprove claims by Ahlborn et al. We simply used his findings as a guide. Both of our robots produced thrust by shedding counter-rotating vortices. However, our robot was allowed to "swim," while their apparatus was stationary. Our robot would have added mass effects and more forces acting on the tailfin, peduncle, and body than in the tail-flip apparatus. These additional forces are at times when the robot has not achieved a steady state velocity. Despite this, a real-time computer simulation of the robot was created after obtaining drag force calculations.

Despite the differences shown graphically, we believe that the equation was useful for our results. We may recalculate the steady state velocities. For some of the heavier weights, we may not achieve the most accurate velocity approximations due to the length of the tank. The relationship between amplitude and thrust force was not clear.

## Optimizing gaits

Since the experimental thrust force is a function of velocity, we can assume that the optimal gaits at different frequencies will be equal. When thrust and efficiency are equally
important, we find the best motions at the same gaits. It is clear that efficiency made the difference. Optimization lowered the phase angles by ten degrees in some cases. We noticed that the data became increasingly unpredictable at the higher frequencies. Using Pareto optimization at varied constraints may give us several critical gaits for our robot.

## Chapter 6, Conclusions

We have learned how to control our robot within certain parameters. Obviously, this robot was not as advanced a swimmer as a real fish. However, we believe our experiments have brought us a closer understanding of aquatic locomotion.

The use of Multiobjective Optimization found the best motion for our robot under a constraint. Taking a graduate course in linear programming and non-linear programming would make this easier to model. An introductory course in fluid dynamics would also help.

Currently, we plan to modify the transmission, anodize the body, and redo experiments. We may try experiments with various tailfin shapes, i.e. lunate, crescent moon shaped. The use of different tailfin shapes moving to a larger aquarium may prove to be advantageous for data accuracy. More degrees of freedom will be added in future experiments. The velocity, efficiency, and drag experiments will be repeated with a modified version of the robot. Additionally, calculations of absolute efficiency will be made.

This research has helped improve our current understanding of robotic swimming. We can control the velocity, efficiency, and thrust force produced by the robot within certain parameters. Hopefully, many future applications in military defense, satellite communication, subterranean exploration, "fishing", and others will become available with the advent of a freeswimming robotic fish.

## List of symbols

| $\mathrm{F}_{\mathrm{x}}$ | thrust force |
| :--- | :--- |
| $\pi$ | pi $(=3.14159 \ldots$. . |
| K | water entrainment constant of 40 |
| $\rho$ | density of water (approx. $\left.1000 \mathrm{~kg} \mathrm{~m}^{3}\right)$ |
| h | submerged height of the tailfin |
| A | amplitude of tail tip deflection |
| $\mathrm{A}_{\mathrm{p}}$ | amplitude of the peduncle |
| $\mathrm{A}_{\mathrm{t}}$ | amplitude of the tailfin |
| $\theta$ | joint angle |
| $\theta_{\mathrm{p}}$ | joint angle of the peduncle |
| $\theta_{\mathrm{t}}$ | joint angle of the tailfin |
| f | frequency |
| $\phi$ | phase difference angle |
| $\phi_{\mathrm{p}}$ | phase angle of the peduncle |
| $\phi_{\mathrm{t}}$ | phase angle of the tailfin |
| $\omega$ | angular velocity |
| \#\#P | phase angle |
| \#\#\# | frequency |
| fps\# | forward velocity |
| T | thrust force |
| D | drag force |
| hmax | maximum deflection of the peduncle and tailfin |
| hmin | minimum deflection of the peduncle and tailfin |
| joutp | actual encoder angles of the peduncle |
| joutt | actual encoder angles of the tailfin |
| lp | length of the peduncle |
| lt | length of the tailfin |

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