# Effects of burst-and-coast duty cycle on collective behavior in a fish school model

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Collective behaviour course research seminar report

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**Burst-and-coast swimming is a common mode of locomotion among fish. Its asynchronous decision making process significantly affects interactions between fish and collective behavior within a school. Our project expands upon a paper that modeled burst-and-coast swimming and studied its long-term collective behaviour, but modeled the burst phase as an instantaneous impulse. We intend to investigate the effects of this simplification on collective behavior as well as the effects of intermittent movement and asynchronous decision making in general by varying the duty cycle and number of decisions per burst.**

Collective behavior | Burst-and-coast | Fish school model

## Introduction

The behavior of individual fish in a group is strongly influenced by social interaction, resulting in collective behaviors such as swarming, schooling and milling. These behaviors have been extensively studied [1, 2] and reproduced using continuous motion models.

However, continuous motion is not the typical mode of locomotion for many species of fish. Instead, many species use burst-and-coast swimming [3] where movement is composed of two cyclical phases: the burst phase, during which the fish decides on a direction (based on the aforementioned social interactions) and rapidly accelerates towards it; and the coast phase, during which the fish passively glides and does not actively attempt to change its speed or heading outside of deceleration due to drag. The ratio between the duration of the burst phase and the total durations of both phases is known as the duty cycle [4].

We build upon a paper by Wang et al. [5] which models the behavior of *Hemigrammus rhodostomus* using agents that implement burst-and-coast swimming and analyzes the long-term collective behavior of large groups of such agents. One of the simplifications made by the model is to treat the burst phase as an instantaneous event due to its short duration compared to the coast phase [6], which is equivalent to a duty cycle of 0%. We will introduce additional parameters to model a non-zero duty cycle and study its effects on the collective behavior.

**Related work.** Lin et al. [7] researched the effect of perturbations on the behavior of schools of fish based on the burst-and-coast model. The perturbations were modeled as a slight modification of the attraction and alignment strength of a subset of fish in the population. Their findings showed that larger groups of fish (N = 100) are much more sensitive to perturbations than smaller groups (N = 25 or N = 50) across most combinations of attraction and alignment strength.

The paper we're expanding upon is based on work by Calovi et al. [6] that also implements a burst-and-coast model for the same species of fish. This paper used raw data obtained by capturing the movement of fish in enclosed tanks using a camera, along with domain knowledge about the specific species of fish, to model the movement of fish during the kick and glide phases. They also separated the drives of avoiding the wall of the tank and interacting with another (neighboring) fish.

## Methods

We re-implemented the model from the original paper [5] in Python. We then extended it with two additional parameters that model a non-zero duty cycle.

**Base model.** The original burst–coast model consists of a repeated cycle:

1. **Heading selection:** Before each burst, the fish computes a new heading based on random noise, attraction and alignment to its $k = 1$ or $k = 2$ most influential neighbors.
2. **Burst phase (kick):** The fish updates its heading and samples a random kick time and length.

3. **Coast phase:** The fish now moves along a straight path for the duration and length of its kick, with an exponentially decreasing velocity.

4. **Repeat:** Once the fish reaches the end of its coast phase, it immediately selects a new heading and begins a new burst.

**Extended model.** The extended model introduces two key parameters: the duty cycle $\omega$ and the number of decision steps $n_\omega$. This transforms the motion from discrete jumps to continuous velocity integration, which is a more realistic representation of fish locomotion.

***Duty cycle.*** When a new swimming cycle beings, its total duration $\tau$, is split into burst and a coast phase:

$$\tau_{\text{burst}} = \omega \cdot \tau$$
$$\tau_{\text{coast}} = (1 - \omega) \cdot \tau$$

At low duty cycles ($\omega \approx 0$), we expect the behavior of the extended model should resemble the behavior of the base model. At higher duty cycles, the velocity will not immediately begin to decrease when a new heading is selected.

***Number of decision steps.*** The parameters $n_\omega$ controls the granularity of decision making during the burst phase. It dictates how many times a fish re-evaluates social forces and adjust it's direction within a single burst.

**Evaluation Metrics.** We use three metrics to evaluate collective behavior. These will also be used to compare our results with the original model. The first one is *Group Dispersion*, representing the average square of distance from the barycenter (i.e. how much the fish are spread out in space). The second one is *Group Polarization*, which is the measure of how varied the headings of different fish are. Lastly, the *Milling Index* quantifies the degree of how much the fish are swimming around a barycenter in a circular fashion. We will use the exact same metrics as the original paper with the goal of producing comparable results:

**Group Dispersion:**

$$D(t) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \|\mathbf{u}_i(t) - \mathbf{u}_B(t)\|^2}$$

where $\mathbf{u}_i(t)$ refers to position of fish $i$ at time step $t$, $\mathbf{u}_B(t)$ refers to position of barycentre and $N$ refers to the number of fish.

**Group Polarization:**

$$P(t) = \left\| \frac{1}{N} \sum_{i=1}^{N} \frac{v_i(t)}{\|v_i(t)\|} \right\|$$

where $\mathbf{v}_i(t)$ refers to the velocity vector of fish $i$ at time step $t$.

**Milling Index:**

$$M = \left| \frac{1}{N} \sum_{i=1}^{N} \sin\left(\bar{\theta}_w^i(t)\right) \right| .$$

where $\bar{\theta}_w^i = \bar{\phi}_i - \bar{\theta}_i$ and $\bar{\phi}_i$ is the angle of the fish's heading and $\bar{\theta}_i$ is the angle of the fish's position, both with respect to the barycenter as the coordinate origin.

These metrics allow for classification of ordered schooling, milling, swarming, and disordered phases.

**Experiments.** We first verified that our implementation of the base model matches that of the original paper. We varied the attraction strength ($[0, 0.6]$, discrete step 0.05) and alignment strength ($[0, 1.2]$, discrete step 0.1), collecting the averages of all three key metrics over 20 simulations for each set of parameters. Each simulation had $N = 100$ fish and stopped at $200000 = 2000 \times N$ kicks. We performed this experiment for both $k = 1$ and $k = 2$.

To study the effects of the new duty cycle ($\omega$) and decision steps ($n_\omega$) parameters, we collected the three key metrics while varying $\omega$ and $n_\omega$. Attraction strength was set to 0.22, alignment strength was set to 0.6 and $k$ was set to 1. We only performed one simulation for each set of parameters with $N = 50$, stopping at 50000 kicks.

We performed one set of experiments with $\omega \in [0.1, 0.9]$ (discrete step 0.1) and $n_\omega = 5$, and another with $\omega = 0.5$ and $n_\omega \in [1, 9]$ (discrete step 1).

## Results

**Base model.** Figure 1 shows the results of the experiment we performed to verify the correctness of our base model. The values are nearly identical to those in the original paper, although our experiment was performed with a lower resolution in terms of attraction and alignment strength.

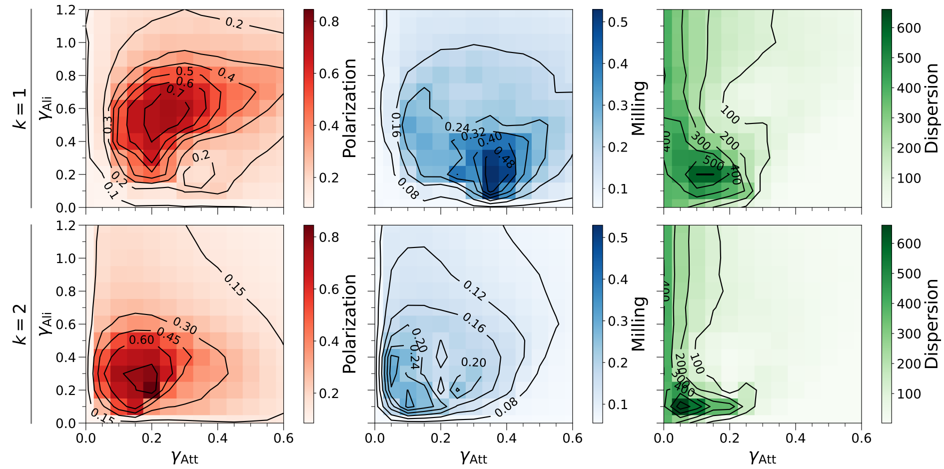
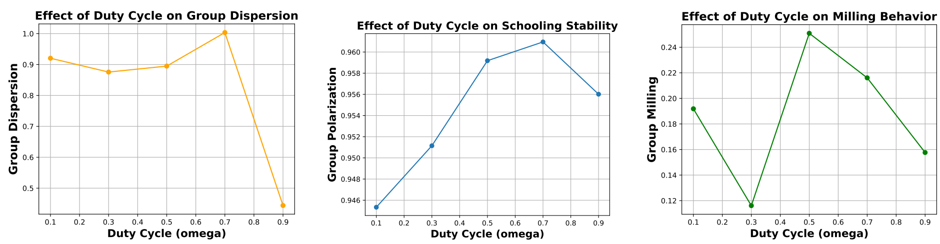



**Figure 1.** Polarization (red), milling (blue) and dispersion (green) values for different combinations of attraction strength ($\gamma_{\mathrm{Att}}$), alignment strength ($\gamma_{\mathrm{Ali}}$) and number of neighbors that influence heading selection ($k$). Each value is an average of 20 runs with different seeds, with each run lasting $2000 \times N = 200000$ kicks. Metrics are only collected after $1000 \times N$ kicks to reduce the influence of initial conditions.

### Extended model.

***Duty cycle.***

- Low $\omega$ ($\leq 0.3$): These states have the lowest polarization and (almost) highest dispersion among the tested values, which is as expected. This comes from short bursts and long coasts, which provide fewer opportunities for coordinated group correction. The group is less cohesive and less aligned.
- High $\omega$ ($\geq 0.7$): At high duty cycles, fish are swimming almost continuously. Our results show a dramatic decrease in group dispersion, which indicates that the school becomes much more compact and cohesive. Polarization also remains high.




**(a)** Dispersion **(b)** Polarization **(c)** Milling

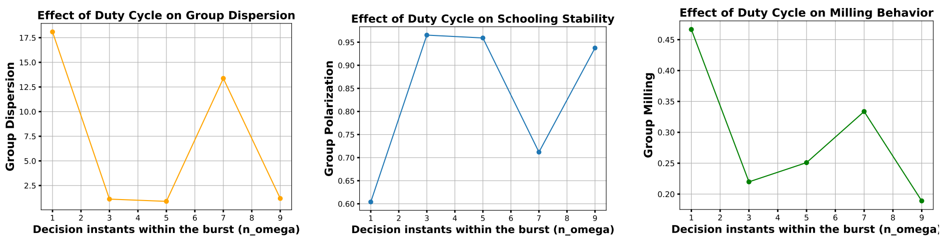
**Figure 2.** Side-by-side comparison of dispersion, polarization and milling for different values of $\omega$.

Our current findings, shown in Figure 2, reveal a complex relationship between duty cycle $\omega$ and collective behavior. Group polarization peaks around $\omega = 0.7$, suggesting that an optimal balance exists between active swimming and passive coasting for maintaining school alignment. However, group dispersion suddenly drops after $\omega = 0.7$, which would indicate that near-continuous swimming forces the agents into a much tighter formation.

***Number of decision steps.*** So far we have performed a parameter sweep with a fixed duty cycle ($\omega = 0.5$) to investigate its effect on schooling stability.

- $n_\omega = 1$: This represent a single burst, making the implementation discrete as opposed to continuous. The fish makes a single decision and commits to that heading for the entire burst. This prevents any corrective maneuvers that the agents would otherwise try to do.

- $n_\omega \geq 5$: This approximates a continuous, smooth turn. It allows agents to make multiple small adjustments within the burst itself, which should lead to a more stable and robust schooling. Our hypothesis was that increasing $n_\omega$ would increase group polarization and decrease dispersion, as it should allow the group to more effectively adjust to fluctuations and resist fragmentation within the school.




**(a)** Dispersion **(b)** Polarization **(c)** Milling

**Figure 3.** Side-by-side comparison of dispersion, polarization and milling for different values of $n_\omega$.

Our current results (depicted in Figure 3) show a significant increase in school stability when moving from $n_\omega = 1$ to $n_\omega = 3$. At $n_\omega = 1$, the system is highly disordered as we can see that group polarization is at its minimum while group dispersion is at its highest, indicating that the school is fragmenting. This confirms that a single, uncorrected burst decision is insufficient to maintain a cohesive school, or at least makes it less stable.

Upon increasing the decision steps to $n_\omega = 3$, the school becomes more stable. We can observe that based on doubling in the polarization and dispersion dropping immensely. This strongly supports the idea that even a small number of corrective steps during a burst result in a more cohesive and aligned grouping.

However, we get a degradation in both polarization and dispersion, both of which improve when increasing the $n_\omega$ to 9.

## Discussion

We have (re-)implemented a burst-and-coast model and extended it with both a simulation framework and a generalization of the duty cycle. The results we obtained are consistent with those of the original model ([5], see Figure 1). We have also implemented tracking of groups, but we have yet to verify our results with the original. We plan to compare several plots: group dispersion and number of groups with respect to time, and the distribution of the number of groups at the end of several runs.

The extended model has also been implemented but needs further validation and a more systematic analysis, as our preliminary results have revealed some unexplainable behavior and strange dynamics. Our initial parameter sweeps have shown that these extensions do have a profound impact on collective behavior, but we do need more plots and statistical backup to confirm our finds. Our current results are based on single, relatively short ($steps = 50000$) runs, which are highly susceptible to stochastic noise. Therefore our immediate future work will focus on addressing these issue and limitations. First we need to reconfirm the results with our base implementation. Second, we need to do a comprehensive parameter sweep for both the extended parameters and find out how one impacts the other, while also averaging all metrics over multiple independent runs to obtain statistically meaningful results. This systematic approach will allow us to draw meaningful conclusions about the behavior of the extended model and its dynamics.

**CONTRIBUTIONS.** JA implemented the base model. MP implemented the simulation framework. AH implemented the extended model. All authors contributed to the report.

## Bibliography


1. Lopez U, Gautrais J, Couzin ID, Theraulaz G (2012) From behavioural analyses to models of collective motion in fish schools. *Interface focus* 2(6):693–707.
2. Filella A, Nadal F, Sire C, Kanso E, Eloy C (2018) Model of collective fish behavior with hydrodynamic interactions. *Physical review letters* 120(19):198101.
3. Kramer DL, McLaughlin RL (2001) The Behavioral Ecology of Intermittent Locomotion. *American Zoologist* 41(2):137–153.
4. Chao LM, Couzin ID, Li L (2024) On turning maneuverability in self-propelled burst-and-coast swimming. *Physics of Fluids* 36(11):111918.
5. Wang W et al. (2025) Collective phases and long-term dynamics in a fish school model with burst-and-coast swimming. *Royal Society Open Science* 12(5):240885.
6. Calovi DS et al. (2018) Disentangling and modeling interactions in fish with burst-and-coast swimming reveal distinct alignment and attraction behaviors. *PLOS Computational Biology* 14(1):e1005933. Publisher: Public Library of Science.
7. Lin G, Escobedo R, Han Z, Sire C, Theraulaz G (2025) Group size and social interactions' strength determine collective response to perturbation in a model of burst-and-coast swimming fish. *bioRxiv* pp. 2025–07.