Master's Thesis
Department of Mathematics and Computer Science

Biorobotics Lab

Robofish: Real-time adaptive recruitment behaviors for biomimetics robots in live guppy swarms

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Abstract

In this thesis, an adaptive leading behavior model for a biometric robot is proposed to lead a guppy. A series of analyses of fish shoals has been performed to provide the theoretical support for this model. This model uses quantified reactions of fish to the robot as feedback. It is implemented using a state machine. The behavior of this model has been divided into sub-behaviors, while each sub-behavior corresponds to a state of the state machine. The adjustment of the robot's motion is made within most of the state and the transitions of the state dependent on the environment in real time. The results indicate that this model is effective to lead a live guppy.

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Berlin, den 4. July 2017

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Contents

1 Introduction

Leadership behavior is a widespread phenomenon in animal groups on the move such as insect swarms, bird flocks, fish shoals and herds ([1], [2], [3], [4], [5], [6], [7]). Mathematical modeling based on the analysis of observational data is often used to study leadership behavior ([8], [9], [10]). The rules of interaction of individuals have been inferred from observation. (For example, a zonal rule showed that the attraction and repulsion of neighbors for mosquitofish depends on the distance between them [9].) However, these proposed rules have not been tested empirically, as the live individuals are hard to control [11].

Recently, with the help of biomimetic robots, researchers can better understand collective behavior and test their models by interacting with live individuals. For example, robotic cockroaches were used to investigate the cockroach's aggregation behavior [12], a robotic bee was used to analyze the honeybee dance communication [13], and a robotic fish was used to study the social behavior of fish [14].

The swarming animals' individual such as fish can present different personalities in the swarm, but the present biomimetic robots are interactive and cannot adjust their behavior to adapt to the different individual. In this thesis, I design an adaptive behavior model of the robot to lead a guppy. The meaning of the term "adaptive" is that the robot produces and adjusts its actions in real time to adapt the (social) environment. It is different from the interactive behavior model which includes predefined patterns of changes to interact with the environment.

In the following, section 2 introduces the biomimetic robot system that has been used in this thesis. Section 3 introduces the analyses of small shoals (2 fish shoal and 5 fish shoal). Section 4 introduces the design and the implementation of the adaptive behavior model. Section 6 evaluates the proposed model with experiments and section 7 summarizes this thesis and discusses future robot behavior models.

2 Related work

2.1 Robofish system used in this thesis

The biomimetic robot system (*RoboFish*) which is used in this thesis is introduced in [14]. A two-wheeled differential drive robot moves below a (88 x 88 cm) shallow water tank on a transparent platform. The robot carries a neodymium magnet to the bottom side of the tank. A fish replica with a magnetic base is magnetically connected to the robot so that it can be moved by it. There are two tracking systems for this system: *FishTracker* and *RoboTracker*. The *FishTracker* tracks the fish and replica via a camera which is fixed above the tank and gets the two-dimensional (2D) coordinates and orientations of the fish and replica. The *RoboTracker* tracks the robot via a camera which is on the ground facing upwards to the transparent platform. The two tracking systems are deployed in two personal computers. The *FishTracker* sends the shoal-tracking results to the *RoboTracker* via a local area network. The *RoboTracker* sends the motion commands to the robot over a wireless network.

2.2 Other Robofish systems

The earlier *RoboFish* system is introduced in [15]. A fish replica with a magnetic base inside a tank is controlled by a two-dimensional moving platform beneath the tank through the magnetic coupling. The moving platform is connected to a personal computer. To control the fish replica's movement, predefined movement paths are sent from the personal computer to the moving platform.

Another *RoboFish* system is introduced in [16]. It is similar to the system used in this thesis. In this system, a fish replica attached to a magnetic base is moved inside a tank using a mobile robot below the tank. A tracking camera above the tank captures the real-time video for a tracking/control system. The tracking/control system is deployed in a computer workstation. It tracks the fish and replica's position, produces robot movement rules dependent on the tracking data in real time, and sends the control commands over Bluetooth channels to the mobile robot. Two behaviors for the robotic fish have been implemented in [16]. In the first implementation, the robotic fish follows the centroid of a live fish school, and in the second implementation, the robotic fish rushes toward the centroid of a live fish school when a defined condition is reached. However, the both behaviors are not adaptive.

In [17], a new *RoboFish* system is introduced. It is similar to the systems introduced in [16] and [14]. The different part is that a fish-like robot is proposed to replace the solid fish replica. The fish-like robot can swing its tail to mimic the movements of real fish's tail.

3 Analysis of fish shoals

This section describes the analyses of the relative position of the fish, the geometric parameters of two fish, the approach behavior and the leading/-following behaviors of fish. To maintain the consistency of the article, I also give the data pre-processing method for extracting the sub-group from a fish shoal in this section. There is a difference between "shoal" and "school" in this thesis which is described in [18]. The shoal is the fish staying together for social reasons, while the school is the fish swimming in the same direction together. In the following sections, The "school" is also described as "sub-group".

3.1 Relative position distribution of fish

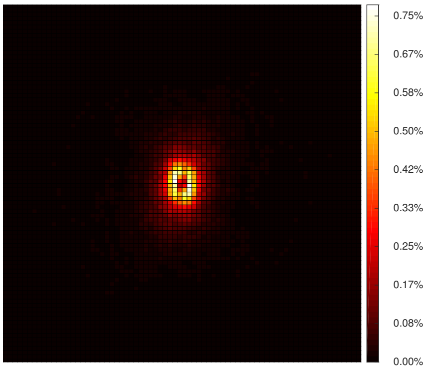
In this section, the relative position distribution in the tracked data of guppy shoal swimming in a shallow water tank is analyzed. This analysis is viewed from two aspects, generality, and individuality.

The analyzed data was collected in an experiment with a five-fish shoal. The experiment video was recorded at 30 frames per second. For every frame t the tracked data contains the horizontal position and the orientation $r(t) = (x(t), y(t), o(t))$ of each fish. The tracked positions of fish were smoothed with the *Savitzky Golay* filter, then the orientations of each fish were recalculated with $atan2$ function:

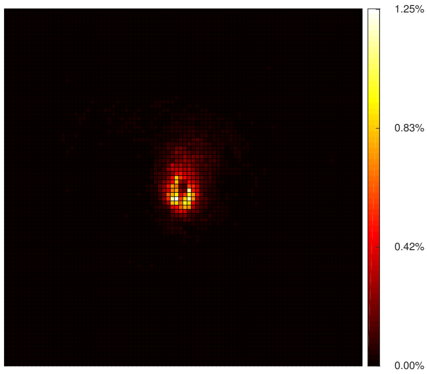
$$o(t) = atan2(y(t+1) - y(t),\ x(t+1) - x(t))$$

Heatmaps are used to show the result of the relative position distribution. The heatmap described a (160 x 160 cm) position space and the position space was divided into the equally-sized square. For the relative position distribution analysis of each fish, the position of $fish(i)$ has been fixed at the center of the position space and the orientation of $fish(i)$ is oriented to the positive direction of Y-axis in Cartesian coordinate system. Then, I the frequency of other fish appearing in each square has been counted. In the heatmap, the color of each square represents the probability that other fish appear in it. The colorbar of the heatmap shows the mapping between the color and the corresponding probability. To get the general relative position distribution of the guppy, the relative position data of each fish have been overlapped to generate a heatmap.

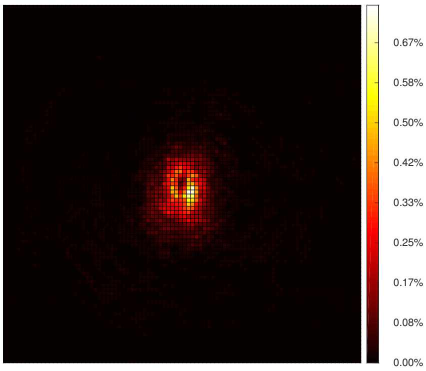
Figure 1 shows the results of the relative position distribution analysis. The general relative position distribution of guppy (Fig. 1.a) shows that the guppies prefer to position themselves around other fish in an ellipse where the major axis is vertical (along the fish vector). They do not often stay too near to other fish or too direct in front of or behind of other fish. The figures 1.b-f show the results of the relative position distribution of each fish in the experimental shoal. It shows that each fish has its own personality in the fish shoal. Other fish often swam in the left rear and right rear of the $fish(1)$, signifying that the $fish(1)$ prefers to be the leader of the fish shoal. The $fish(2)$ often swam in the left front of other fish, this signifies that the $fish(2)$ prefers to be the leader of the fish shoal too but on the left side. The $fish(3)$ often swam behind other fish or swam parallel to other fish but it swam nearer to others. The $fish(4)$ often swam behind other fish in the left rear and right rear. This signifies that the $fish(3)$ and the $fish(4)$ prefer to be the follower of the fish shoal. The $fish(5)$ is different to other fish, it often swam on the left side, in the right front and right rear of other fish. This may signify that the $fish(5)$ prefers to swim in the middle of the fish shoal.



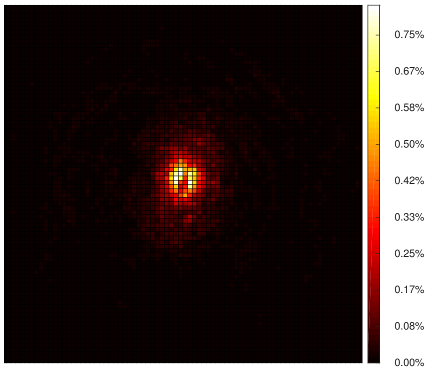
(a) The general analysis



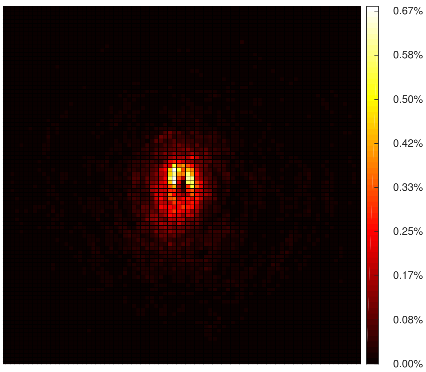
(b) Other fish around fish 1



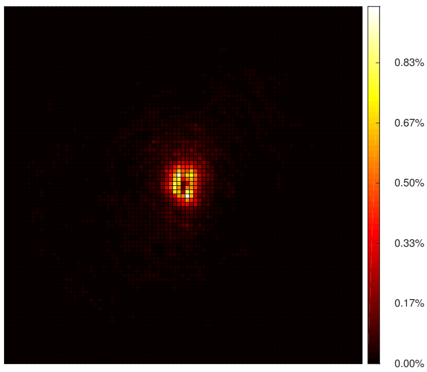
(c) Other fish around fish 2



(d) Other fish around fish 3



(e) Other fish around fish 4



(f) Other fish around fish 5

Figure 1: The distribution positions of fish

3.2 Features of fish pair

In this section, parameters are defined to quantify the position information between two fish in the fish school. These parameters will be used in the following analyses.

- Let d_{ij} denote the *distance* between $fish(i)$ and $fish(j)$.
- Let α_{ij} denote the *included angle* between $fish(i)$ and $fish(j)$, where the *included angle* is the angle between two fish vectors.
- Let β_{ij} denote the *linked angle* from $fish(i)$ to $fish(j)$, where the *linked angle* from $fish(i)$ to $fish(j)$ is the angle between a $fish(i)$ vector and the vector from the $fish(i)$ to the $fish(j)$.
- Let df_{ij} denote the *forward distance* between $fish(i)$ and $fish(j)$, where the *forward distance* between $fish(i)$ and $fish(j)$ is the vertical component of the distance in the orientation of $fish(i)$.

  $df_{ij} = d_{ij} * cos(\beta_{ij})$
- Let ds_{ij} denote the *sideward distance* between $fish(i)$ and $fish(j)$, where the *sideward distance* between $fish(i)$ and $fish(j)$ is the horizontal component of the distance in the orientation of $fish(i)$.

  $df_{ij} = d_{ij} * sin(\beta_{ij})$

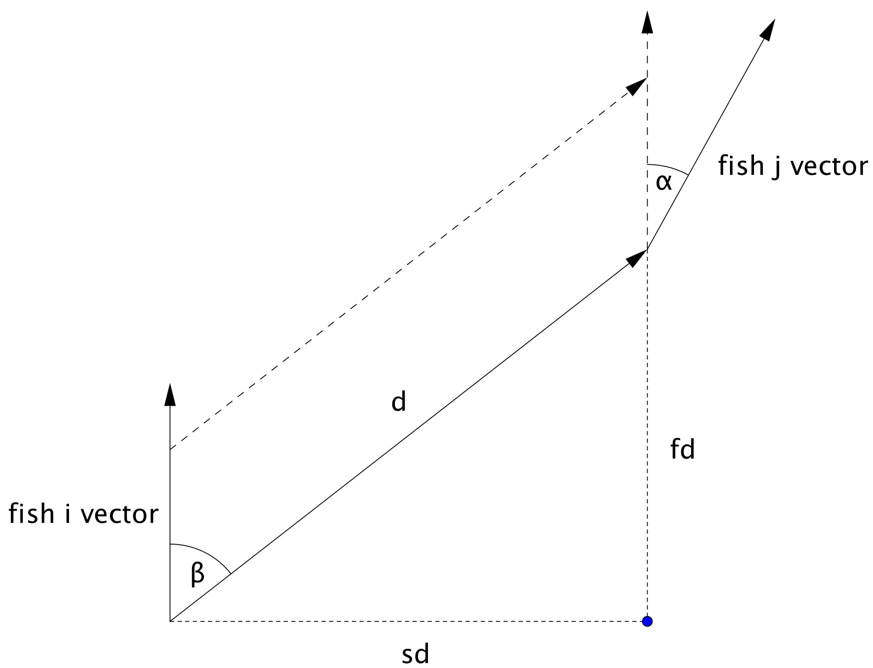


Figure 2: Parameters: d: the distance between fish(i) and fish(j); sd: the sideward distance between fish(i) and fish(j); fd: the forward distance between fish(i) and fish(j); α: the included angle between fish(i) and fish(j); β: the linked angle from fish(i) to fish(j)

3.3 Data distribution of features

In this section, the data distribution of the parameters given in the previous section have been studied. While *forward distance* and *sideward distance* can be calculated by the *distance* and *linked angle*, I only analyze the data distribution of the *distance*, *included angle* and *linked angle*.

The same data as the 3.1 has been used to calculate the distributions of each parameter.

Figure 3 shows the result of the distributions. The *distance* (Figure 3.a) between each fish is between 3 and 25 cm with a probability of 0.65. The *included angle* has a broader distribution, the peak area of the *included angle* between each fish is between 0 and 30 degrees with a probability of 0.38. The distribution of the *linked angle* (Figure 3.c) between each fish is very broad, each bin of the histogram has a similar probability.

The results of the distributions signify that the guppy fish usually swims near other fish even though they do not swim in the same direction. This conclusion can be interpreted by the probabilities too. The probability $P(d < 25)$ is equal to 0.63 and the conditional probability $P(\alpha < 30|d < 25)$ is equal to 0.5, which d is the *distance* and α is the *included angle*.

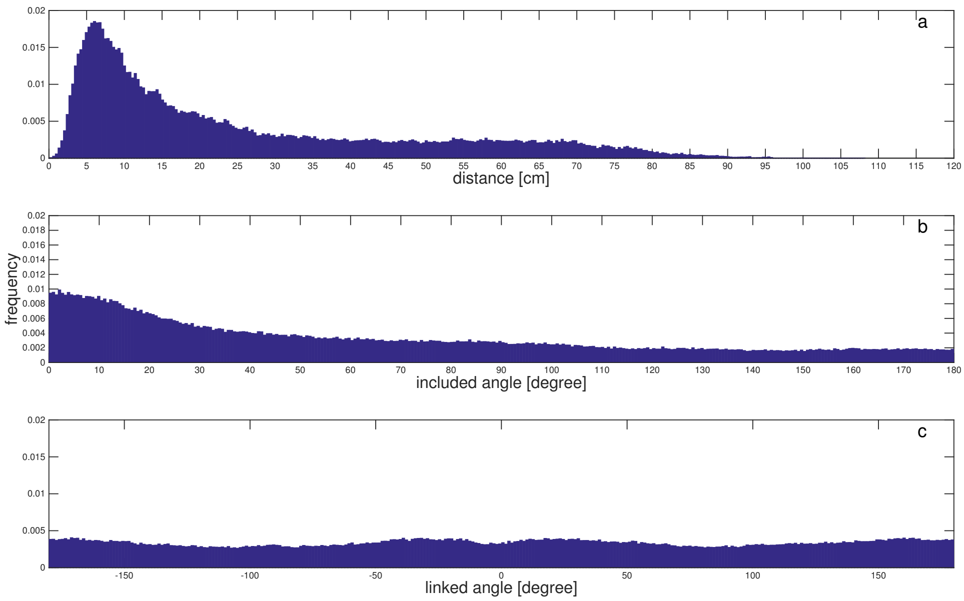


Figure 3: a), the distribution of the distance between every two fish in the fish shoal. b), the distribution of included angle between every two fish in the fish shoal. c), the linked angle between every two fish in the fish shoal.

3.4 Sub-group extraction

To study the leading/following behavior of the guppy fish, I extract the sub-group from the fish shoal. The sub-group is where the fish swim together in the same direction. This group has the leader and the follower. Although it does not contain the information why the fish gather together or disperse, it gives the relative position and the movement information of the leading/following behavior.

In our extraction algorithm, the following is defined:

1. If the *distance* between two fish is less than or equal to d and the *included angle* between two fish is less than or equal to α, then the two fish belong to a sub-group.
2. If the $fish(a)$ and the $fish(b)$ are in the same sub-group, the $fish(b)$ and the $fish(c)$ are in the same sub-group, then the $fish(a)$, $fish(b)$ and $fish(c)$ are in the same sub-group.
3. The sub-group must be last for some time t, otherwise, it will not be extracted as a sub-group.

An adjacency matrix M is used to represent the graph of a fish shoal. Each fish is a point of this graph. If the *distance* between $fish(i)$ and $fish(j)$ is less than or equal to d and the *included angle* between $fish(i)$ and $fish(j)$ is less than or equal to α, then $M(i, j) = 1$, otherwise $M(i, j) = 0$. Hence, the finding of the sub-groups of the shoal is equivalent to the finding of the connected subgraphs in the shoal graph.

Algorithm 1: Sub-Group Extraction

```
input  : Adjacency Matrix M
output: List of connected subgraphs
remainderNode = [];
subGroups = [];
for i = 0 → (number of fish − 1) do
    remainderNode.pushBack(i);
end
while remainderNode is not empty do
    id = remainderNode.back();
    remainderNode.popBack();
    openSet = [];
    openSet.pushBack(id);
    subCloseSet = [];
    while openSet is not empty do
        tempList = remainderNode;
        now = openSet.back();
        openSet.popBack();
        subCloseSet.pushBack(now);
        for it = 0 → (length of tempList − 1) do
            if M[now][it]==1 then
                remainderNode.remove(it);
                openSet.pushBack(it);
            end
        end
    end
    subSwarms.pushBack(subCloseset);
end
```

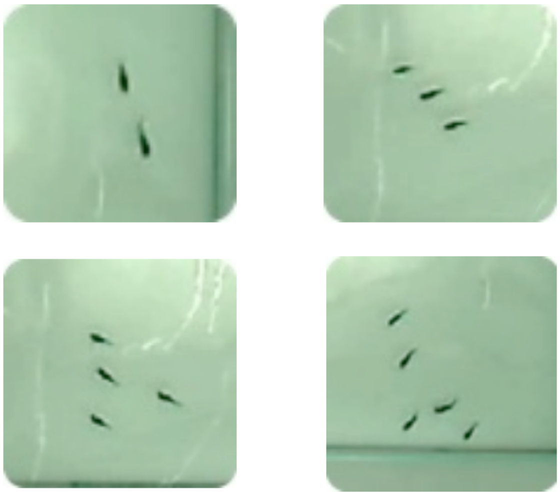


Figure 4: The 2-5 sub-groups extracted by the extraction algorithm, which $d = 10$, $\alpha = 23$. The unit of distance is centimeter, The unit of angle is degree.

3.5 Leading and following behavior in fish pair

In this section, the leading and following behavior of guppy fish will be examined. It is complicated to analyze the leading and following behavior in a big size sub-group of fish. A follower in the middle of a big size sub-group may be the leader of other fish that are at the back of this sub-group. And it is difficult to know whether a fish is following another fish or whether it is following the whole swarm. To simplify this issue, the 2-sub-groups of guppy fish are examined with regards to their leading and following behavior.

The 2-sub-groups that have been analyzed were chosen as follows:

1. The relationship of both fish should remain stable. In observed 2-sub-groups that two fish are jostling for the leader position sometimes. They swim alternately to the front of the other fish. There is no obvious leader or follower in this behavior. Therefore, this behavior is not analyzed in this section.

2. The leading/following motion should last for some time. There is little information in a transitory leading/following motion. Besides that, some transitory leading/following motions may not belong to the leading/following behavior, it just presents the similar motion to the leading/following behavior. For example, it is coincidental that two fish swim nearly toward the same direction and then disperse. The two fish will be selected by our sub-group extraction algorithm as a 2-fish-sub-group but it does not belong to the leading/following behavior. In this case, it will bring the noisy data to our analysis.

The relative position between the leader and the follower is quantified with the follower to leader's *linked angle* and *distance*. The geometrical significance of follower to leader's *linked angle* is which direction the leader is located to the follower. If the *linked angle* equals to $0°$, then the leader locates straight ahead of the follower. If the *linked angle* equals to $\pm 90°$, then the leader is the horizontal side of the follower. The analysis (Figure 5) of the follower to leader's absolute *linked angle* shows that the leader swam between $7°$ and $40°$ to the left/right of the follower with a probability of 0.704. There are also *linked angles* greater than $90°$. This occurs in the turning motion of both fish, where the leader has turned into another direction but the follower not yet. The distribution of the *linked angle* (Figure 6) shows that the follower prefers in the right rear of the leader, This might be because the leader usually swam clockwise along the edge of the tank in the experiment so that the follower could not swim on the left side of the leader. The analysis (Figure 7) of distance shows that the distance between leader and follower is between 3 and 9 cm with a probability of 0.8025. To study the relationship between the distance and the follower to leader's *linked angle*, a 2-dimensional histogram has been generated and the linear regression algorithm was used to estimate the linear relationship between them (Figure 8). The 2-dimensional histogram shows that the short *distance* corresponds to the bigger *linked angle* and the long *distance* corresponds to the smaller *linked angle*. The result of linear regression shows that as the value of *distance* increases, the value of *linked angle* decreases. In another word, the leader and follower swim in a single file when the leader is far from the follower, when the leader and follower are near, they prefer to swim in a diagonal row.

By analyzing many leader trajectories and observing different lead/follow periods, it is expected that the fish in the leading/following behavior change their direction not as often as other behaviors: The variance of orientation change per frame is 0.0721 in leading/following behavior, 0.3918 in all other behaviors (Figure 9). It can be noticed that there is a stop-and-go motion in the leading/following behavior (Figure 10). It can be assumed, that the stop-and-go motion may play an important role in the interaction between leader and follower. The stop phase may give follower the time to react or catch up with the leader (Figure 11).

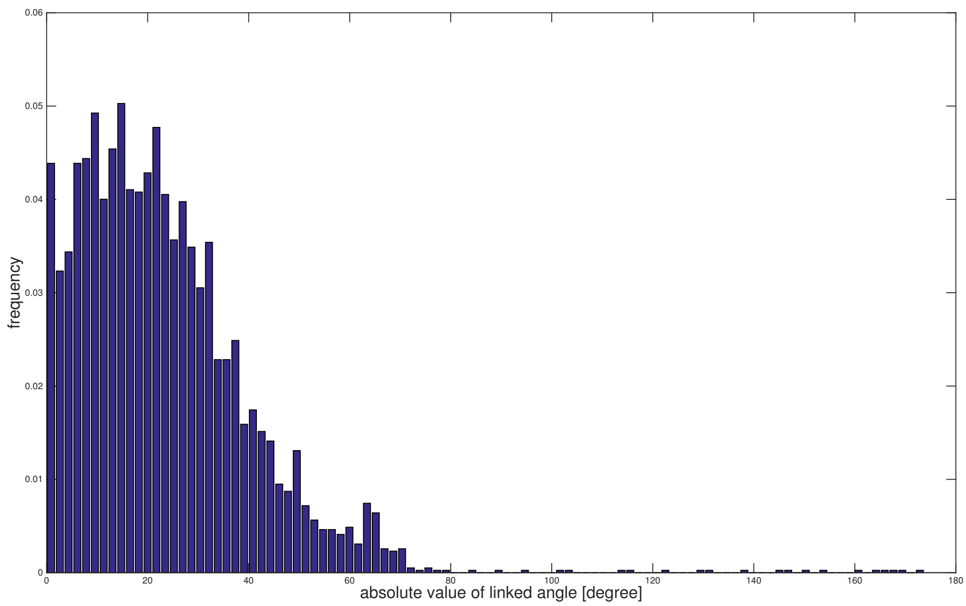


Figure 5: The distribution of follower to leader's absolute linked angle.

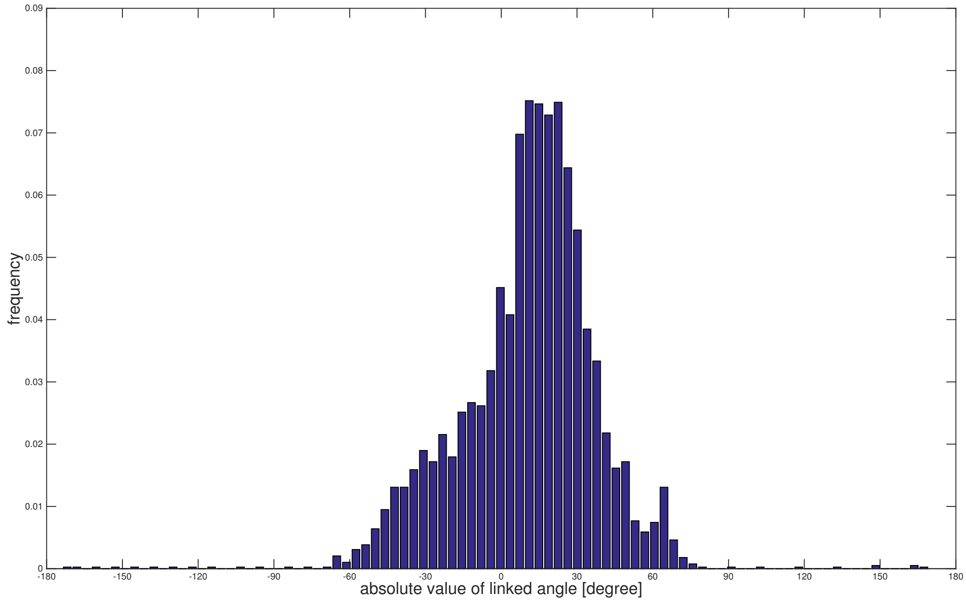


Figure 6: The distribution of follower to leader's linked angle.

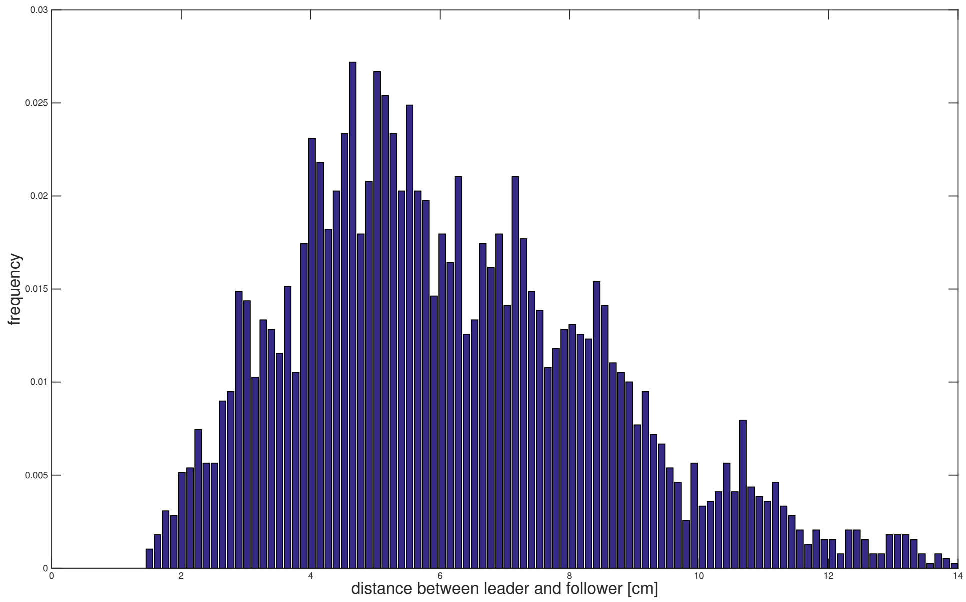


Figure 7: The distribution of distance between leader and follower.

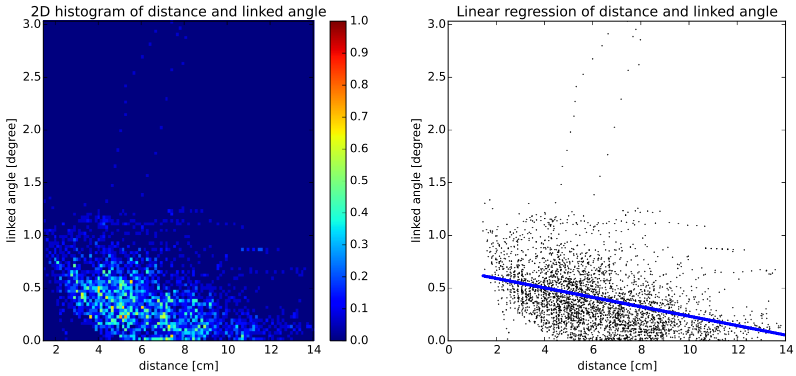
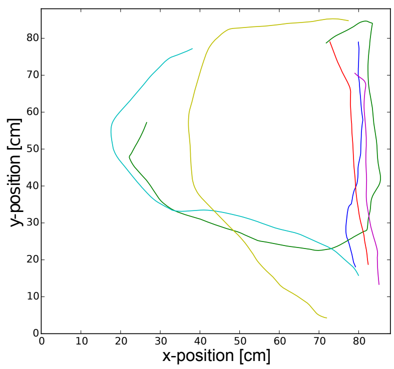
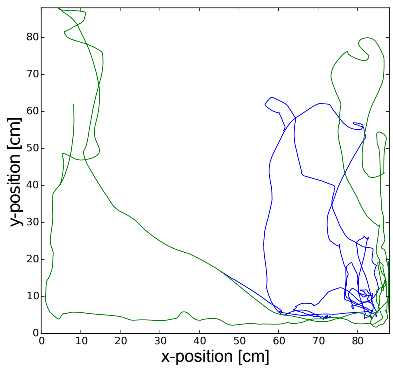


Figure 8: Left: The 2D histogram of distance between leader and follower and the follower to leader's linked angle (unit: radians). Right: The linear regression of distance between leader and follower and the follower to leader's linked angle.(Predicts the *linked angle* value for a given value of *distance*.)



(a) Trajectories of leader in the leading/-following behavior



(b) Trajectories of fish that do not belong to the leading/following behavior

Orientation change	Unit	μ	σ	σ^2	σ/μ
Lead periods	radians/frame	0.0042	0.0721	0.0052	17.028
Other periods	radians/frame	0.0030	0.3918	0.1535	131.484

(c)

Figure 9: Top: Comparison of the leader's trajectories the leading/following behavior to other behaviors. (a): Five trajectories of leader. (b): Two trajectories of the fish that not in the lead/follow movement. (c): The Comparison of the *orientation change* of lead periods to other periods. The trajectories and the *orientation change* were calculated from a consecutive two-fish shoal's tracking data, the video of this two-fish shoal was recorded at 30 frames per second.

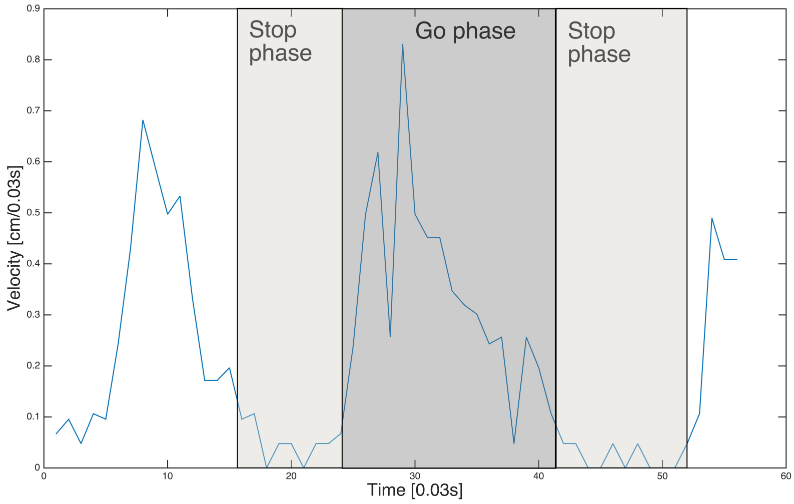


Figure 10: Example of the stop-and-go motion phases of leader.

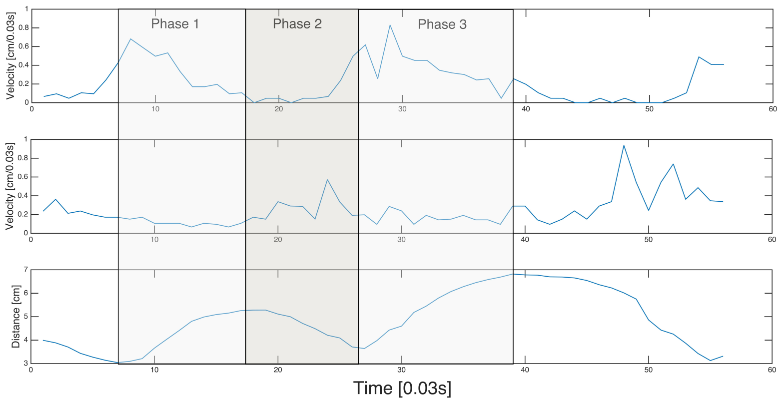


Figure 11: The role of stop-and-go motion in the interaction between leader and follower. Top: The velocity of leader. Middle: The velocity of the follower. Down: The distance between leader and follower. The plots were generated from a nature leading/following behavior. In phase 1, the leader swam, the follower stopped, the distance between leader and follower increased. In phase 2, the leader stopped, the follower swam, the distance decreased. The phase 3 is same as the phase 1. In this interaction, the stop phase of leader gives follower time to shorten the distance between themselves. When the follower catches up with the leader, it waits for the next action of the leader.

3.6 Velocity analysis of approach behavior

The approach behavior is a guppy's behavior in which a guppy swims to another guppy. It is different from the lead/follow behavior because there is no leader. But a lead/follow motion could transition from an approach motion. In this section, it is studied how the approaching fish changes its velocity along the change of the distance between approaching fish and target fish. Eight approaches of motion periods will be extracted, where the distance between the two fish is longer than 40 cm at the beginning of the approach motion. The Figure 12 shows the results of this analysis. The velocity of an approach motion can be divided into two phases, the uniform motion phase, and the decelerating motion. The approached fish swam to the target fish fast at the beginning and then it reduced its velocity when it was near to the target.

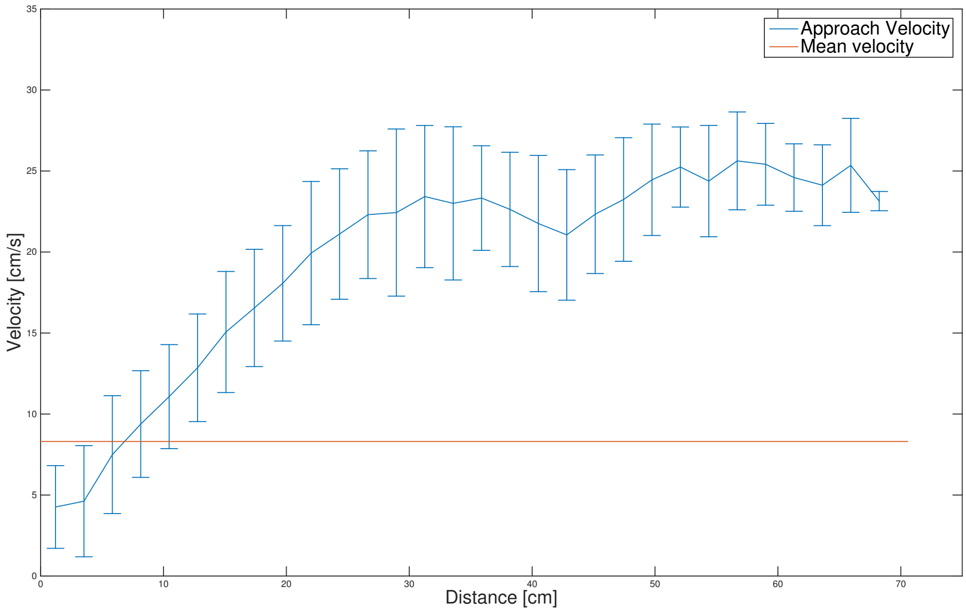


Figure 12: Approach velocity over distance. The red line is the mean velocity of all.

4 Implementation of RoboFish leading behavior

In this section, a model will be supported to implement the leading behavior of RoboFish. The goal of the model is that the robot will lead one fish. There are two important aspects of this model: the lead area and the lead motion. The lead area is fan-shape area in the front of the target fish. It is based on the analysis of the lead fish's relative position (Figure 5, 7). The lead motion is a biomimetic stop-and-go motion based on the analysis of the lead fish motion (Figure 10). Presumably, this motion could attract the target fish to want to follow. Figure 13 shows the architecture of the system of the robot's leading behavior. The FishTracker and RoboTracker provide the positions and orientations of the target fish and the robot to the state machine, detector and RoboFish perception modules. The state machine module is the core of this system. It controls the behavior of the robot. The RoboFish perception module calculates the feedback of the target fish to the robot. The state machine uses that information to adjust the robot's behavior. The detector module is used to detect the position of the robot in the tank, for example in the corner or near the edge. The controller receives the order from the state machine and controls the motion of the robot.

A complete lead process of this model is: The robot approaches the target fish then swims to the front of the target fish and does the lead motion. In the following subsections, the *lead area*, the *lead motion*, the *RoboFish perception module* and the *state machine module* will be described.

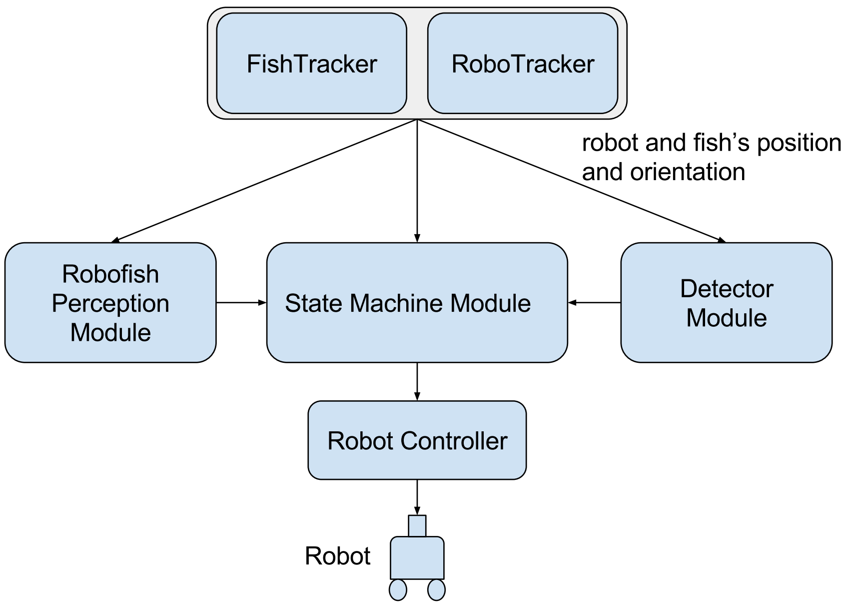


Figure 13: The system architecture diagram of the robot leading behavior system.

4.1 Lead area and lead motion

The lead area is a fan-shape area in the front of the target fish (Figure 14). It is defined by three parameters: minimum distance, maximum distance and breadth angle.

- Let LA_MIN_Dist denote the minimum distance.
- Let LA_MAX_Dist denote the maximum distance.
- Let LA_BA denote the breadth angle.

Where the prefix "LA" is the abbreviation of "lead area".

The robot is in the lead area if the distance between the robot and the target fish is greater than or equal to LA_MIN_Dist and lesser than or equal to LA_MAX_Dist and the $abs(linked\ angle)$ from target fish to the robot is lesser than or equal to LA_BA.

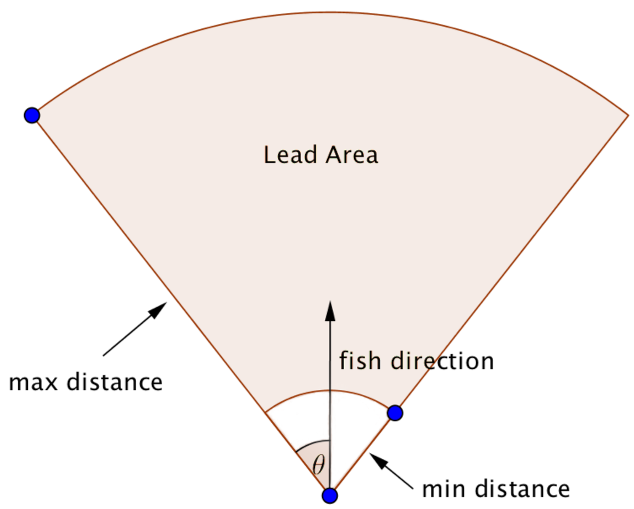


Figure 14: The graph of lead area. θ is the breadth angle.

The lead motion imitates the stop-and-go motion that is introduced in 3.5. It was implemented by a motion path. The motion path stores the consecutive target points of the robot. The distance between any two adjacent target point is equal. The robot swims from one target point to another (go phase), when the robot arrives at one target point, it stops for a short time (stop phase) and then goes on swimming to the next target point. There are three parameters in the lead motion: distance, stop time, maximum velocity.

- Let LM_Dist denote the distance between two adjacent target points.
- Let LM_ST denote the stop time.
- Let LM_MV denote the maximum velocity of the movement between two adjacent target points.

Where the prefix "LM" is the abbreviation of "lead motion".

4.2 RoboFish perception

In this section, a model is proposed, which evaluates and formulates the reaction of the target fish to the robot.

4.2.1 Follow perception

The *follow perception* is used to detect whether the target fish follows the robot.

The term $followValue$ is used to formulate the following behavior:

$$followValue(t) = \frac{Approach\ Distance}{Absolute\ Distance}$$

Where $followValue(t)$ is the follow rate of the target fish to the robot at frame t, and is calculated from the relative motion between the robot and target fish in the last Δt frames. The *Absolute distance* is the displacement of target fish in the last Δt frames. The *ApproachDistance* is the projection of the displacement vector of the target fish in the last Δt frames onto the vector from the target fish to the robot at the frame $t - \Delta t$.

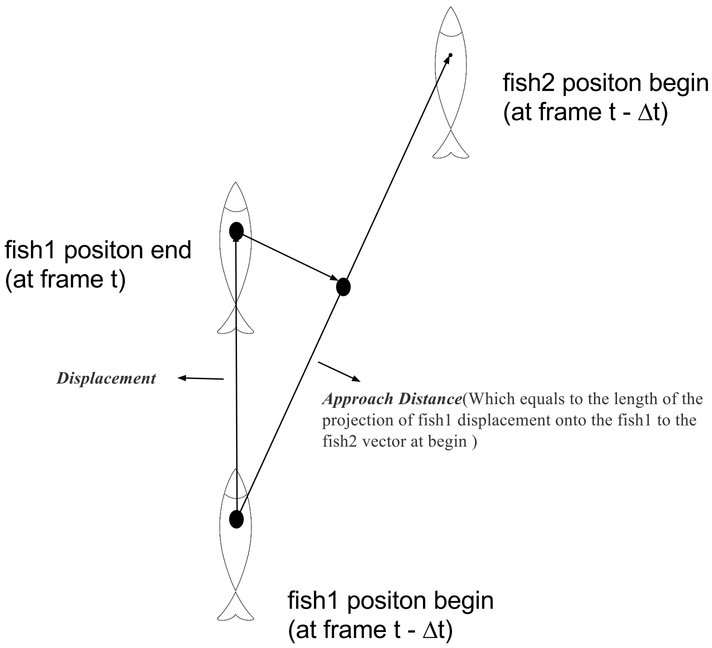


Figure 15: The approach distance of the fish1 to the fish2.

4.2.2 Fear perception

The *fear perception* is used to detect whether the target fish fears the robot. The idea of fear detection is that if the target fish fears the robot then it may make some abnormal movements. An abnormal movement may be swimming away from the robot quickly or change its direction suddenly. I break down the fear detection problem into two parts, the first is detecting whether the robot impacts the target fish, and the second is detecting whether the target fish does abnormal reflex actions regarding the robot.

4.2.2.1 The impact the robot has on the fish

The *distance controller* and the *normalized robot approach distance* have been used to represent the effect the robot has on the target fish.

The *distance controller* is a Boolean variable. It is defined by one parameter: minimum distance.

- Let $dc(t)$ denote the value of *distance controller* at frame t.

- Let FP_MIN_Dist denote the minimum distance.
- Let d denote the distance between the robot and the target fish at frame t.

Where the prefix "FP" is the abbreviation of "fear perception".

$$dc(t) = \begin{cases} 1 & \text{if d} \leqslant \text{FP\_MIN\_Dist} \\ 0 & \text{else} \end{cases}$$

The *distance controller* is an important tool, because if the distance between the robot and the target fish is big, then the robot cannot impact the target fish.

The *normalized robot approach distance* is a variable between zero and one. It describes to what extend the robot approaches the target fish. It is defined by two parameters: *approach distance lower bound* and *approach distance upper bound*.

- let $NRAD(t)$ denote the *normalized robot approach distance* at frame t.
- Let $RAD(t)$ denote the *approach distance* of the robot at frame t.
- Let FP_RAD_LB denote the *approach distance lower bound*.
- Let FP_RAD_UB denote the *approach distance upper bound*.

$$NRAD(t) = \begin{cases} 0 & \text{if RAD(t)} \leqslant \text{FP\_RAD\_LB} \\ 1 & \text{if RAD(t)} \geqslant \text{FP\_RAD\_UB} \\ \frac{RAD(t) - RAD\_LB}{FP\_RAD\_UB - FP\_RAD\_LB} & \text{else} \end{cases}$$

4.2.2.2 The reflex actions of the fish regarding the robot

The *normalized fish escape distance* and the *normalized fish angle difference* are used to represent the fish's reflex actions with regard to the robot.

The *normalized fish escape distance* is a variable between zero and one. It describes to what extend the target fish escapes from the robot. The *escape* *distance* at frame t is equal to the distance between the robot and the target fish at frame t minus the distance at frame $t - \Delta t$. The *normalized fish escape distance* is defined by two parameters: *escape distance lower bound* and *escape distance upper bound*.

- Let $NFED(t)$ denote the $normalized\ fish\ escape\ distance$ at frame t.
- Let $FED(t)$ denote the *escape distance* of the fish at frame t.
- Let FP_FED_LB denote the *escape distance lower bound*.
- Let FP_FED_UB denote the *escape distance upper bound*.

$$NFED(t) = \begin{cases} 0 & \text{if FED(t)} \leqslant \text{FP\_FED\_LB} \\ 1 & \text{if FED(t)} \geqslant \text{FP\_FED\_UB} \\ \frac{FED(t) - FED\_LB}{FP\_FED\_UB - FP\_FED\_LB} & \text{else} \end{cases}$$

The *normalized fish angle difference* is a variable between zero and one. It describes to what extend the fish changes its direction in the last Δt frame. Two parameters define it: *angle difference lower bound* and *angle difference upper bound*.

- Let $NFAD(t)$ denote the $normalized\ fish\ angle\ difference$ at frame t.
- Let $FAD(t)$ denote the $angle\ difference$ of the fish at frame t.
- Let FP_FAD_LB denote the $angle\ difference\ lower\ bound$.
- Let FP_FAD_UB denote the $angle\ difference\ upper\ bound$.

$$NFAD(t) = \begin{cases} 0 & \text{if FAD(t)} \leqslant \text{FP\_FAD\_LB} \\ 1 & \text{if FAD(t)} \geqslant \text{FP\_FAD\_UB} \\ \frac{FAD(t) - FAD\_LB}{FP\_FAD\_UB - FP\_FAD\_LB} & \text{else} \end{cases}$$

4.2.2.3 Fear value

The *fear value* is used to formulate the fear degree of the target fish. It is a number between zero and one, zero meaning that the target fish has no fear, and one meanings that the fear of the target fish is maximum. The $fearValue(t)$ is the *fear value* of the target fish at frame t. It is calculated by $dc(t)$, $NRAD(t)$, $NFED(t)$ and $NFAD(t)$:

$$fearValue(t) = dc(t) \times NRAD(t) \times (w_\alpha \times NFED(t) + w_\beta \times NFAD(t))$$

Where w_α and w_β are the weight of *normalized fish escape distance* and *normalized fish angle difference*, they are used to show the contributions of the *normalized fish escape distance* and the *normalized fish angle difference* to the *fear value*.

4.3 State machine

A state machine controls the leading behavior. The state machine has five states. Each state is responsible for a specific action. The initial state is the first state when the leading behavior is started, it is used to reset the parameters of the robot to default settings. The other four states are the distance feedback approach state, the swim to the front state, the lead state and the avoid state.

4.3.1 Distance feedback approach state

In the approach state, the robot approaches the target fish. By analysis of the approach motion of the guppy (Figure 12), the velocity of the robot can be controlled depending on the distance between robot and target fish with a piecewise linear function. Four parameters calculate the approach velocity: minimum distance, maximum distance, slope a and intercept b.

- Let $v(d)$ denote the velocity of the robot v at distance d.
- Let SA_MIN_Dist denote the minimum distance.
- Let SA_MAX_Dist denote the maximum distance.

Where the prefix "SA" is the abbreviation of "state approach".

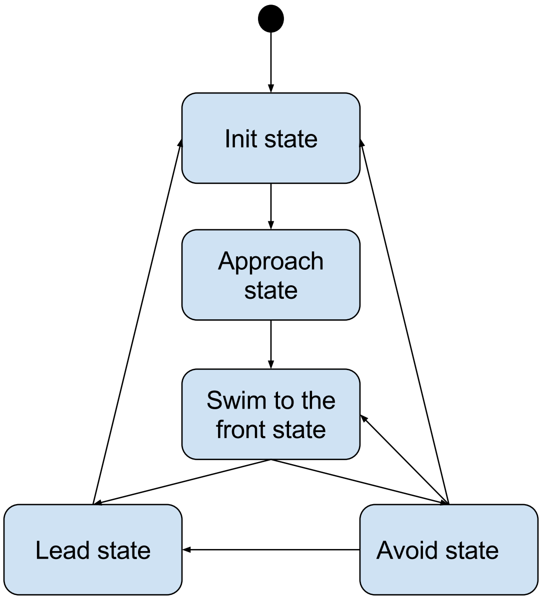


Figure 16: The state machine diagram

$$v(d) = \begin{cases} 0 & \text{if d} \leqslant \text{SA\_MIN\_Dist} \\ \text{SA\_VC} & \text{if d} \geqslant \text{SA\_MAX\_Dist} \\ a \times d + b & \text{else} \end{cases}$$

Where SA_VC is a constant speed, a is the slope and b is the intercept of the linear function.

4.3.2 Swim to the front state

The mission of the robot in this state is swimming to the lead area of the target fish. It is implemented by a target point in the lead area. The robot swims to the target point in this state, but it does not need to arrive at the target point, as it is just used to bring the robot to the lead area. Two parameters calculate the target point: SF_TP_Dist and SF_TP_ALA, where SF_TP_Dist is the distance between the target fish and the target point, SF_TP_ALA is the absolute linked angle from the target fish to the target point. The prefix "SF" and "TP" are the abbreviations for "state front" and "target point".

There are two candidate target points: left target point and right target point because the absolute linked angle calculates the target point. The one close to the robot will be selected as the target if the both points are in the tank sub-area. If there is a candidate target point out the tank sub-area and another one in the tank sub-area, the point in the tank sub-area will be selected. If all the two candidate points are outside the tank sub-area, they will be rotated around the target fish, the left point to the left, the right point to the right, until they are all inside of the tank sub-area. Then, the point with smaller rotation will be selected as the target point. If the angle of rotation of both points is equal, then the one close to the robot will be selected.

The tank *sub-area* is a square area inside of the tank. It is used to avoid collision between the robot and wall of the tank. Let h denote the height of the tank. Let w denote the width of the tank. Let TSA_Dist denote the distance between the tank edge and the sub-area where the prefix "TSA" is the abbreviation of "tank sub-area". The coordinates of the four vertexes of this square are: (TSA_Dist,TSA_Dist), (TSA_Dist, $h - TSA\_Dist$),($w - TSA\_Dist$, $h - TSA\_Dist$) and ($w - TSA\_Dist$, TSA_Dist).

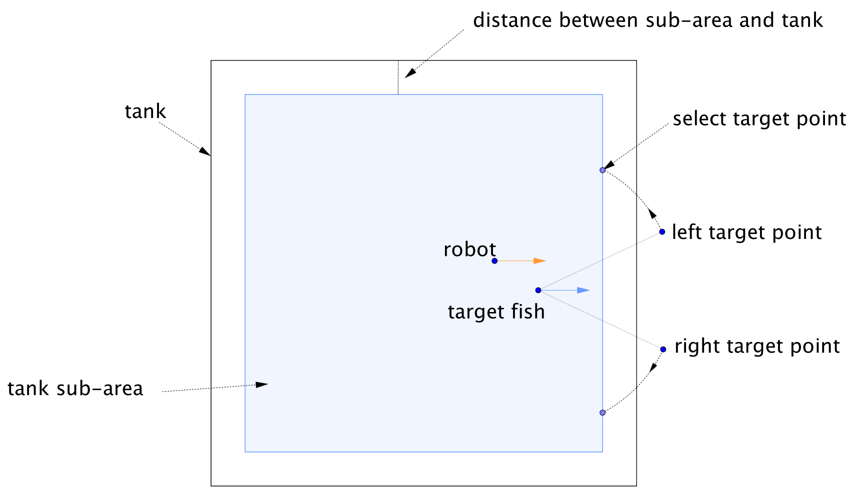


Figure 17: The tank sub-area and an example of the choice of target point.

4.3.3 Avoid state

The avoid state is a subsequent state of *swim to the front state*. If the robot's motion in the *swim to the front state* causes fear for the target, the robot will swim away from the target fish to avoid further damage. The initial target point of the robot in the avoid state is calculated by the last target point of *swim to the front state* and $fearValue$. Let SF_LTP denote the last target point of *swim to the front state*. If the SF_LTP is on the left of the target fish, I rotate it d degrees to the left around the target fish. If the SF_LTP is on the right of the target fish, it will rotated d degrees to the right around the target fish. The d is calculated by the $fearValue$:

$$d = \ fearValue \times (90 \ - \ SF\_TP\_ALA)$$

The robot swims along the vector from the robot to the initial target point in this state. If the robot reaches the edge of the *tank sub-area* it turns back to the *tank sub-area* and goes on straight swim.

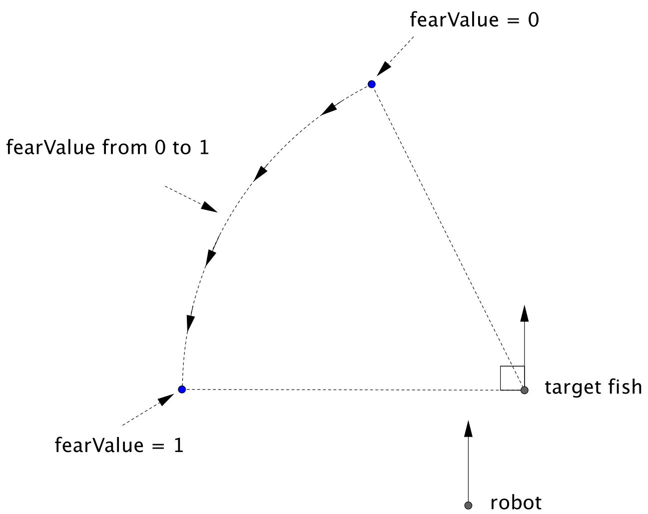


Figure 18: The selection of avoid state initial target point. The initial target point is changing along the arc, depending on the value of *fearValue*.

4.3.4 Lead state

In the lead state the behavior of the robot is independent, it is not affected by the target fish. The robot does the lead motion which is introduced in the section above. The robot swims straight ahead and turns when it's near the edge of the tank sub-area. The initial orientation of the robot is its orientation in the end of *swim to the front state*. The reason that the robot will go in a straight motion is derived from the analysis: 3.5 (Figure 9). This analysis shows that the fish does not often change its direction in the leading/following behavior.

4.3.5 Transition of the state machine

- **Approach state to swim to the front state**: If the distance between the robot and the target fish is less than or equal to d_{ap2f} and lasts t_{ap2f} seconds.

- **Swim to the front state to lead state**: If the robot in the target fish's lead area lasts t_{f2l} seconds.

- **Lead state to initial state**: If the robot not in the target fish's lead area lasts t_{l2i} seconds.

- **Swim to the front state to avoid state**: If the $fearValue$ of the target fish is greater than or equal to fv_{f2ad}.

- **Avoid state to lead state**: if the robot is in the target fish's lead area.

- **Avoid state to swim to the front state**: If the robot is in the target fish's *side area* (Figure 19) and the $fearValue$ of the target fish is lesser than or equal to fv_{ad2f}.

- **Avoid state to initial state**: If the robot in the avoid state lasts t_{ad2i} seconds.

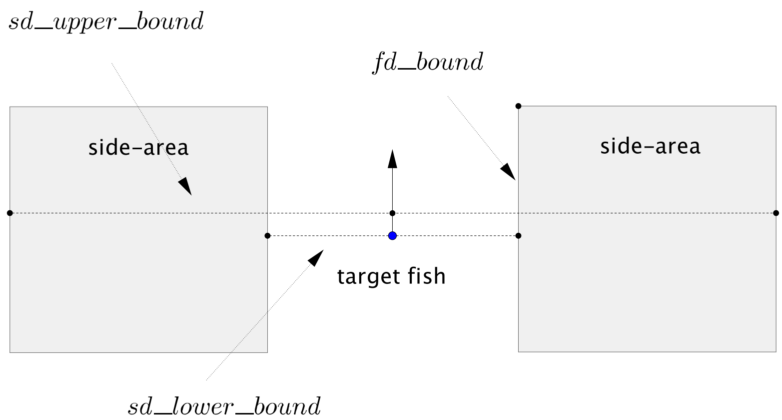


Figure 19: The side area of the target fish. If the *sideward distance* between the robot and the target fish is greater than or equal to sd_lower_bound and less than or equal to sd_upper_bound, the absolute *forward distance* less than or equal to fd_bound, then the robot is in the side area of the target fish.

5 Experiments

A new model has been implemented to compare with the model introduced in the previous section. The new model is the same as the previous model, but instead of the distance feedback approach state, the velocity of the robot in the approach state is a constant which equals to SA_VC. In another word the new model is a less feedback or less adaptive model. To distinguish between the both models, the original *feedback model* and the new *no feedback model* are named. In the experiments, ten guppies have been tested for the two models, each individual's experience lasted five minutes. Details of the experiment parameters are listed in the appendix.

Four metrics have been relied upon for quality evaluation: the mean follow duration, the mean distance between the robot and the target fish when the target fish follow the robot, the mean $fearValue$, and the percentage of each state duration. The definition of the fish following the robot in this evaluation is: 1) the robot is in the *lead state*, 2) the target fish's $followValue$ is greater than 0.85, 3) the distance between the robot and the target fish is lesser than $30cm$ (Figure 20).

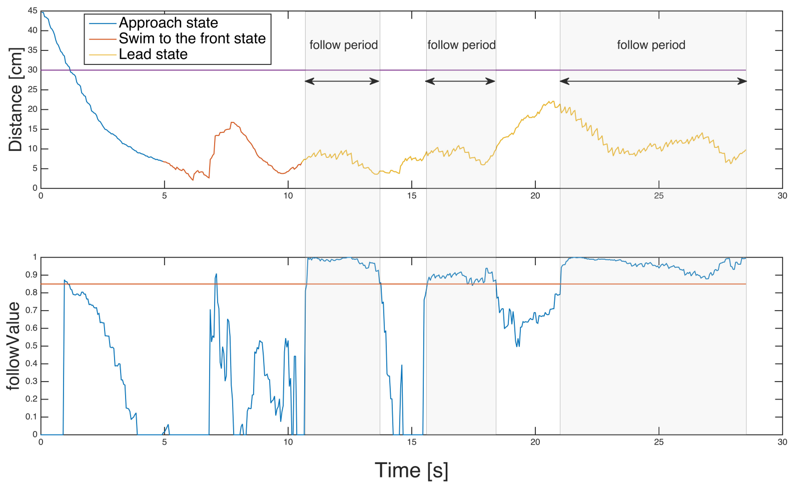


Figure 20: Example of the follow period extraction. (Top) The distance between the robot and the target fish. (Down) The $followValue$ of the target fish.

5.1 Results

Both models succeeded in leading guppies

The guppies spent 759 seconds (25.3% of the total experiments time) to follow the robot in the *feedback model* and 185 seconds (6.7% of the total experiments time) in the *no feedback model*.

Guppies spent more time to follow the robot in the *feedback model*

A comparison of the mean follow duration (Figure 21.a) shows that the robot's leading time in the *feedback model* was significantly longer than the *no feedback model* (t-test, $p = 0.0222$).

The mean distance between the target fish and the robot were similar for both models when the target fish followed the robot

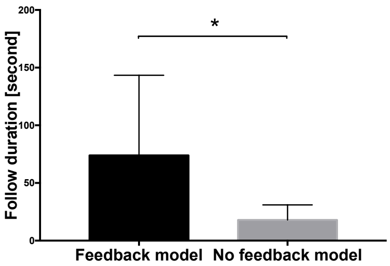
There was no significant difference in the mean distance (Figure 21.b) between the *feedback model* and the *no feedback model* when target fish followed the robot (t-test, $p = 0.2887$).

Robot caused less fear in the *feedback model*

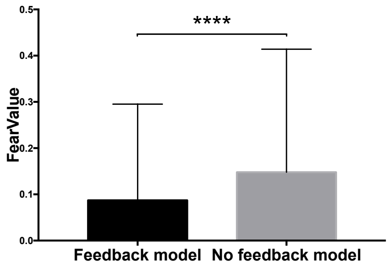
A comparison of the mean $fearValue$ (Figure 21.c) shows that the mean $fearValue$ of guppies in the *feedback model* was significantly smaller than the *no feedback model* (t-test, $p < 0.0001$).

Robot in the *feedback model* stayed longer in lead state

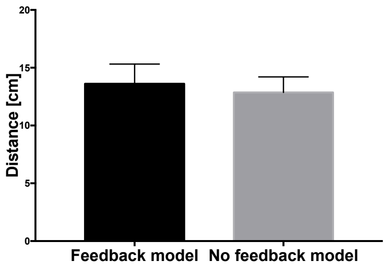
In the *feedback model*, the robot was in the approach state 29% of the running time, 10% in the toFront state, 57% in the lead state, 4% in the to avoid state. In the *no feedback model*, the robot was in the approach state 24% of the running time, 23% in the toFront state, 36% in the lead state, 17% in the avoid state (Figure 21.c). By comparison, although the robot spent more time to approach the target fish in the *feedback model*, it could be easier to swim to the front of the target fish and to stay longer in the lead state.



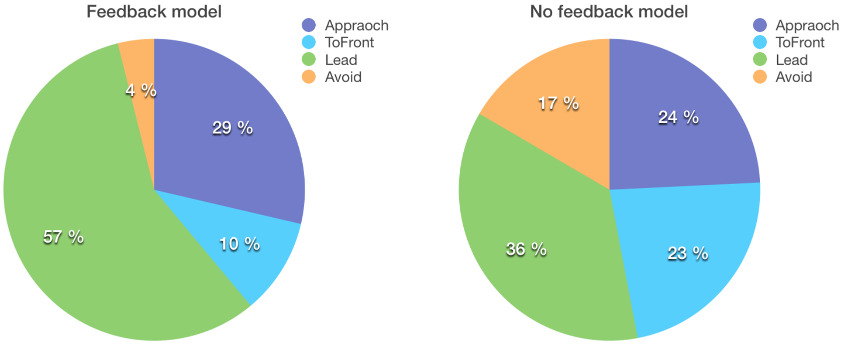
(a) Mean follow duration ± SD



(b) Mean fearValue ± SD



(c) Mean distance ± SD



(d) State pie chart

Figure 21

6 Discussion and outlook

I analyzed the leading/following behavior of small shoal and proposed a robot behavior model to lead a single guppy based on the analyses. Four metrics have been proposed to evaluate this model. The principal metric is the follow duration, indicating whether this model is effective to lead a live guppy. The mean $fearValue$ is an important metric to evaluate the acceptance of the robotic fish by live guppies. The mean distance shows the distance between the fish and the robotic fish in the leading/following behavior. The percentage of each state duration shows the efficiency of this model: the greater the proportion of the lead state, the more efficient is the model. In experiments, an less adaptive model was proposed to compare with the original model. The results indicate that my robot behavior model is effective to lead a live guppy and the adaptive model is more effective, acceptable and efficient than the less adaptive model. The results also show that the total follow duration, the mean $fearValue$ and the percentage of each state duration are effective metrics. The *mean distance* is no good metric to compare advantages and disadvantages of the robot behavior model.

Although this robot behavior model successfully led a guppy, it cannot learn and improve its behavior through multiple runnings with live fish. The artificial neural network, deep learning and reinforcement learning algorithms may be used to develop better robot behavior models for the future. The $followValue$ and the $fearValue$ proposed in this thesis may be useful to those algorithms as efficient parameters.

7 Appendix

The parameter values of the model are determined by the results of the fish shoals analysis and the experience of experiments.

	Parameter	Unit/Ann.	Value
Lead area	LA_MIN_Dist	cm	2
	LA_MAX_Dist	cm	25
	LA_BA	°	45
Lead motion	LM_Dist	cm	8
	LM_ST	s	0.22
	LM_MV	cm/s	11
Fear perception	FP_MIN_Dist	cm	15
	FP_RAD_LB	cm	0
	FP_RAD_UB	cm	3
	FP_FED_LB	cm	0
	FP_FED_UB	cm	4
	FP_FAD_LB	°	0
	FP_FAD_UB	°	17
	w_α	–	0.8
	w_β	–	0.2
State machine	SA_MIN_Dist	cm	6
	SA_MAX_Dist	cm	40
	SA_VC	cm/s	11
	a	–	0.8
	b	–	0.2
	SF_TP_Dist	cm	16
	SF_TP_ALA	°	30
	TSA_Dist	cm	6
	d_{ap2s}	cm	8
	t_{ap2s}	s	0.6
	t_{f2l}	s	0.5
	t_{l2i}	s	9
	fv_{f2ad}	–	0.75
	fv_{ad2f}	–	0.3
	t_{ad2i}	s	9
	sd_upper_bound	cm	6
	sd_lower_bound	cm	15
	fd_bound	cm	8

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