Freie Universität Berlin

Fachbereich Mathematik und Informatik

Masterarbeit

im Studiengang
"Bioinformatik Master of Science"

Thema:

Implementation of a behavior module for a biomimetic robot
to simulate leading in fish shoal

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Berlin, 17.10.2018

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Berlin, den 17.10.2018

Acknowledgments

I would like to thank the people from Biorobotics Lab and Jens Krause's Lab for the opportunity to work with them in the RoboFish project and their kind working environment.
Special thanks go to Tim Landgraf, David Bierbach, Hai Nguyen and Hauke Mönck for directly supporting me in my work and helping to shape and improve the zone model to its current state.

Contents

1 Abstract

Collective behavior research is a vast and complex field. Understanding the varying interaction patterns between members of a group and simulating them with the help of models is a difficult and long process. But in recent years biomimetic robots gave rise to new chances of evaluating and verifying the state of the art in this field.

Leading is one key aspect in collective behavior. Deciphering its mechanisms would gain the ability to immensely influence a whole group in a desired direction which in turn can be used in experimental setups for investigating social interactions e.g. foraging.

A biomimetic robot can be perfectly exploited for this research question. An implemented model will instantly verify in wet lab experiments whether its underlying logic is giving back the desired reaction from real living beings.

In this work, the model is a modified version of Couzin's zone model, adapted for leading behavior. In this model it is assumed that individuals try to keep the members of their group in a close zone around them. It got implemented in the framework of the RoboFish project as an automatic behavior module and got tested with guppies (*Poecilia reticulata*).

The results show that leaders can keep larger distances to other members of the group before forced to draw closer again. Followers do need to stay near other individuals to feel comfortable inside the group. Because of this distance relationship, leaders have more freedom in their choices and need to keep less track about the actions of the other members. As the robot is allowed to remove itself for longer distances before it is forced to travel back to the fish than the average guppy, it was indeed able to take the role of a leader several times.

As this work only presents an implementation which concentrate on few core aspects, the module gives promise for more insight into the mechanisms of leading with future expansions considering additional factors in its code base.

2 Introduction

In nature, one of the most successful strategies to get an advantage in nature comes from forming groups, so called flocks, swarms or shoal. Cooperating can give the group a lead in e.g. protection from external dangers, exploitation of food resources, raising the next generation as single individuals do not have the needed physical or mental capabilities to achieve the same results.

The positive aspects of this strategy can be seen in the vast distribution in species, from complex societies of ants and bees to the spontaneous arising of bird flocks and fish shoals, down to the organization between cells.[1]

New insights found in collective behavior research give rise to new application in other fields as well. There exists a certain overlap between the mechanisms of collective behavior of animals and human psychology. Data inferred from other species can be compared with data in the psychology field. As rules found in other species could also play a role in human interaction, especially in times of high stress when danger is present and fast decision making is needed. This knowledge could help in preventing or improve handling certain situations with negative impact.[2]

Even in more unrelated fields the insight in collective behavior enjoy a certain popularity. As an example, in optimization several algorithms were implemented based on marking the shortest route to food sources with pheromone strategies of ants[3] or group interaction of social spiders[4] to find solution in difficult to solve mathematical problem.

To research the behavior of animals, in the traditional approach, researchers observe species in their natural environment or in special lab setups with low amount of noise to infer concepts from the observed data and build models to describe a logic that serves this concepts. As a downside these are complicated to prove as for a long time there was no direct way to apply them on living beings. One solution lies in computer simulations which can test if the logic of the models are giving back the same pattern in the computer output as they were observed in nature. Those algorithms can take into consideration features like collision, velocity and flock centers to describe group formation.[5] and using mathematical methods e.g. statistical[6, 7] and numerical[8] simulations.

But as the agents in a simulation are always following the underlying logic, there is no guarantee that real living beings would really react the same way at certain stimuli as the programmed agent which inherited a lot of assumptions from the designer. Additionally a simulation is always covering only certain aspects of reality which were deemed most important by the designer and though is ignoring factors which may actually playing an important part in the decision-making. This dilemma can be solved by biomimetic robots. If their appearance is convincing for the real species and gets accepted as one of their own, it has the chance to integrate itself inside a swarm as an agent. As there is full control of the robots behavior, the logic of models can be implemented and tested in reality and not only in virtual space. As there is now full control over one member of the group, the reaction of the remaining individuals give the needed feedback if the model can successfully describe the behavior patterns. A model with natural description would recreate observation done before. An unnatural model would cause unexpected reactions. Hence, biomimetic robots give the opportunity to turn dry lab experiments like computer simulations into wet lab experiments. In recent years, biomimetic robots became a popular approach to get influence in certain systems in varying way and got applied e.g. for birds, frogs, lizards.[9, 10]

In research fish are an established model system. Fish species are diverse and adapted to a lot of different environments.[11] They are easily housed without much complications and get a lot of offsprings, keeping up the population over generations conveniently. For behavior research, it is useful that they show a rich set of reaction, hence a lot of data is collectible.[12] A lot of varying setups for experiments can be generated in labs without too much costs.

In Biorobotics Lab, the RoboFish project uses a biomimetic robot to integrate a 3D-printed dummy into a fish shoal of guppies. The project was already able to implement different types of following behaviors. On the other side of the spectrum of collective behavior, leading is still untouched. It would open up new ways of influencing a shoal and testing social mechanics e.g. leading to food resources or danger avoidance.

This works goal is to implement a simple zone model based on three zones around an individual, each describing another behavior towards members that enters the respective zone and though forming a swarm of individuals. Although not using the term zone itself, The prototype of this idea was first proposed by Aoki back in 1982.[13] Back then the ability to form a shoal was based mainly on two types of behaviors: approaching and parallel orientation. Further it was assumed that each action is independent of the past time steps. All individuals only move only on a horizontal plane, completely ignoring the vertical axis and limiting the setting to two dimensional space. A gamma distribution is used to determine random velocities for the artificial fish in a computer simulation. Despite not calling it zones himself, Aoki already described a zone like structure around the fish with the help of distances, one for approaching the other for avoiding if too close proximity. But it was not considered in a full circle, concerning the restricted field of vision that does not allow the fish to notice members behind their back. Indeed, test simulations resulted in the forming of artificial fish shoals.

Later, the model approach was picked up by Couzin et al and and got redescribed in form of zones.[14] Avoidance to sustain minimal distance is regulated by a zone of repulsion. If leaving the zone of repulsion, the fish tends to align itself with the other members. Aggregation gets covered by the zone of attraction which enforces approaching. To keep the formation of the shoal during a longer period of time, neighbors are tried to be kept inside the zone of orientation while keeping aligned to each other. This model is now able to simulate artificial fish in a three dimensional space. The simulations successfully recreated swarm formations, also showing known behavior from nature like milling. In mills fish tend to align with far of neighbors, forming a torus like structure.[15]

An adapted implementation of Couzin's version respective to leading added to the RoboFish framework finally gives the possibility to verify this concept in wet lab experiments with real fish.

3 State of the art

Besides the RoboFish system from Biorobotic Lab, other fish robot systems exists with different strategies concerning hardware and (behavior) software implementation. The respective labs are examining different kinds of fish species. As there are quite few of them, two were picked out from the list to be shortly presented.

One of them is the FishBot With a similar setup to the RoboFish.[16, 17, 18, 19] It consists of a 1 x 1 meter large water tank in which fish and the RiBot are placed. The RiBot has the appearance of a fish and serves as a dummy. It is equipped with additional hardware functionalities like moving its tail which allows for sending more social signal to the fish than merely moving around. It can be moved through magnetism by a wheeled robot which drives on a platform below the tank. Cameras are tracking the positions of fish from above and of the robot from below. The group works with zebrafish (*Danio Rerio*). They implemented a collective motion model which uses velocity vectors for speed determination and probability distribution to randomly pick orientations. In their study they showed how several robots were mixing with real fish and are forming a swarm for a longer amount of time as well a simple following behavior.

Kim et al uses a slightly different strategy for the robot movement as it is controlled not on an additional floor below the tank but through the help of a robotic platform.[20] There the movement of the dummy can be changed on a x-,y- and z axis. Their approach to integrate the robot is a so called close loop control system. Instead of implementing a behavior based a set of inferred rules as mentioned before, the system analyses the behavior of the real fish visually and then gives feedback to the robot how to interact. They also are working with zebrafish.

The Biorobotics Lab in cooperation with Jens Krause's Lab is researching the swarm behavior mainly on guppies by providing the software and hardware for the RoboFish system.[21, 22, 23]

The setting consists of a water filled tank with the dimension of 1 x 1 meter. Below the tank is an additional floor with the same dimensions on which the robot can freely drive around, see Figure 1.

The Robofish is a small wheeled robot. All its hardware is composed inside a box. On top of it is a pole with a magnet which reaches to the bottom of the tank so that in can interact with the magnet of the dummy fish which in turn can be moved around in the water tank.

The dummy fish is a 3D-printed model of a guppy which was then colorized. One important aspect are the eyes. Glass eyes were glued on the fish dummy. It turned out that they need to have a large size which will raise the acceptance of the dummy from the real fish. If the eyes are too small the attraction of the robot is low and fish are less willing to interact with it.[24]

It should be also mentioned that on the lower side of the robot are LEDs filmed by a camera . This are needed to track the live position of the robot on the floor. To track the position of the fish at the same time, a second camera films the water tank from above.

The images of the cameras are send to two computers. On each of them a software from Biorobotics Lab is running: FishTracker and RoboTracker. The FishTracker is tracking the position of all fish

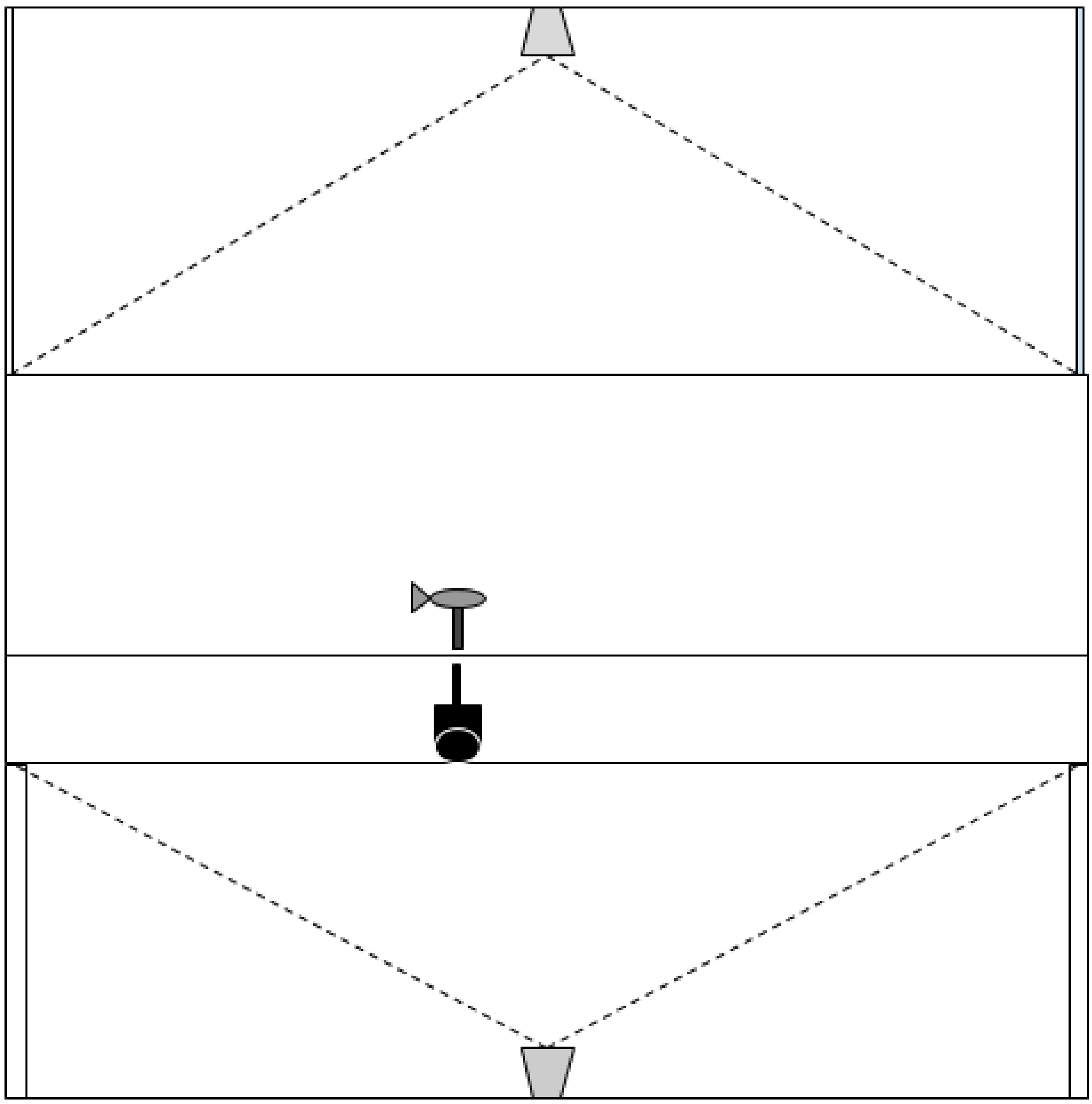

Figure 1: Hardware setup of RoboFish. A 3D-printed dummy model is moved around inside a 1 x 1 meter water tank by a wheeled robot on the lower floor through magnetism. On the ground is a camera which tracks the LED lights of the robot from below. On the top of the setup, a second camera is filming the events inside the water tank for tracking purposes of the fish. The image data is processed live by two computers

and the dummy on the images. As the tank is completely white, the fish appear as dark ellipses on a light background. Therefore the image can be binarized by putting all dark pixel values, which are presumably the fish, to white and all remaining values to black. The fish then look like white blobs on a black background and can be detected by a blob detection algorithm which gives back the center of the ellipses as position.

Each position gets an ID to specify each fish. From frame to frame, these IDs are kept to the same fish identity by using the simple nearest neighbor approach or a particle filter. This way the system can differentiate and follow each fish over time. Data is saved with IDs, positions,angles and frame numbers.

The RoboTracker analyses the LED position of the robot on the image. The LEDs are appearing as white blobs on black background. Therefore its position on the image can be detected as well by a simple blob detection and recomputed into abstract world coordinates. To filter out the dummy position from the FishTracker, all fish positions are compared with the robot position with nearest neighbor and the closest candidate gets removed from the list of fish.

The graphical interface allows the user to customize the settings of the behavior of the robot quite flexible. Having changeable motor settings, movement types of the robot and a list of predefined automated behavior modules.

So far those behavior modules contain simple following behaviors. The robot approaches the fish and tries to take its place in the swarm e.g by using the centroid of the swarm as its position.

Now the next step it is time to integrate leading behavior as an additional possibility to interact with a swarm. The robot shall not only orientate itself on other fish but also get the opportunity to do its own decision based on a set of rules without losing its membership inside the swarm. Therefor leading would be a first good approach.

A first possible implementation for leading can be done by Couzin's model of three zone further described in the next section of this work. The idea of the zone model is fairly simple but still quite flexible as there are a few tunable parameters which can greatly influence the reaction of fish. It would give a good starting point for first experiments examining the mechanisms of leadership.

4 Methods

4.1 Implementation

The model consists of three different sized circle shaped zones. The fish is the center point of each of those zones. Each zone defines a different behavior executed by the fish depending on the absolute distance between the individuals. They are described as follows:

1. Rejection zone: If there is any fish in this zone the center fish will try to move away while keeping a specific angle to all members as defined in Couzin's simulation[25], here with p_i as the position vector and t as time step iterating over individuals: $-\sum \frac{p_j(t)-c_i(t)}{|p_j(t)-c_i(t)|}$

2. Comfort zone: The fish will try to keep swarm members in this zone. The own position or trajectory must be adjusted if others are leaving this zone. It is located right after the rejection zone.

3. Attraction zone: This is the outermost zone. Individuals in this zone are preferred to be in the comfort zone and therefore the fish has to reduce the distance by approaching them.

Those zones apply for both, robot and fish. In the current module the default scenario let's the robot look for the nearest neighbor to itself to which it then drives to a focal point around the chosen target fish to get both robot and fish into each others comfort zone and form a swarm together.

A geometrical representation can be found in Figure 2.

Different sizes of the zone on the robot leads to different reaction of fish. It is important to optimize all parameters so that the robots behavior resembles the natural analog the most. Only then can the fish be influence as desired. The size of all zones is defined by a radius with its center point always equaling the corresponding fish itself.

The size of the attraction zone is not tunable in our setting as the water tank is rather small so that every part that is not covered by the rejection and comfort zone automatically falls into the responsibility of the attraction zone. Note that in scenarios with much larger space, e.g. an ocean, this would be different as the fish most likely will not consider any individuals that are to far away because a) it cannot build up a sense of relationship and does not consider the other as part of the swarm any more or b) the other is out of his perceptibility.

The rejection zone was chosen to be a radius of 3 cm as our data of tracked fish swarms suggest that this is the natural distance kept between individuals.[26] A smaller distance would force the real fish of keeping more distance to the robot as it would always close in too much. That would result into a fleeing scenario. A too large zone would not allow the robot to approach the fish close enough and swarm can be formed between the robot and fish as the robot may not be in the comfort zone of the fish while the fish never had a chance to accept the robot as a member if its swarm.

The comfort zone is a more complicated parameter to tune. An assumption is that individuals will keep a sense of group relationship if neighbors are not farther away than four body length.[27, 28, 29]

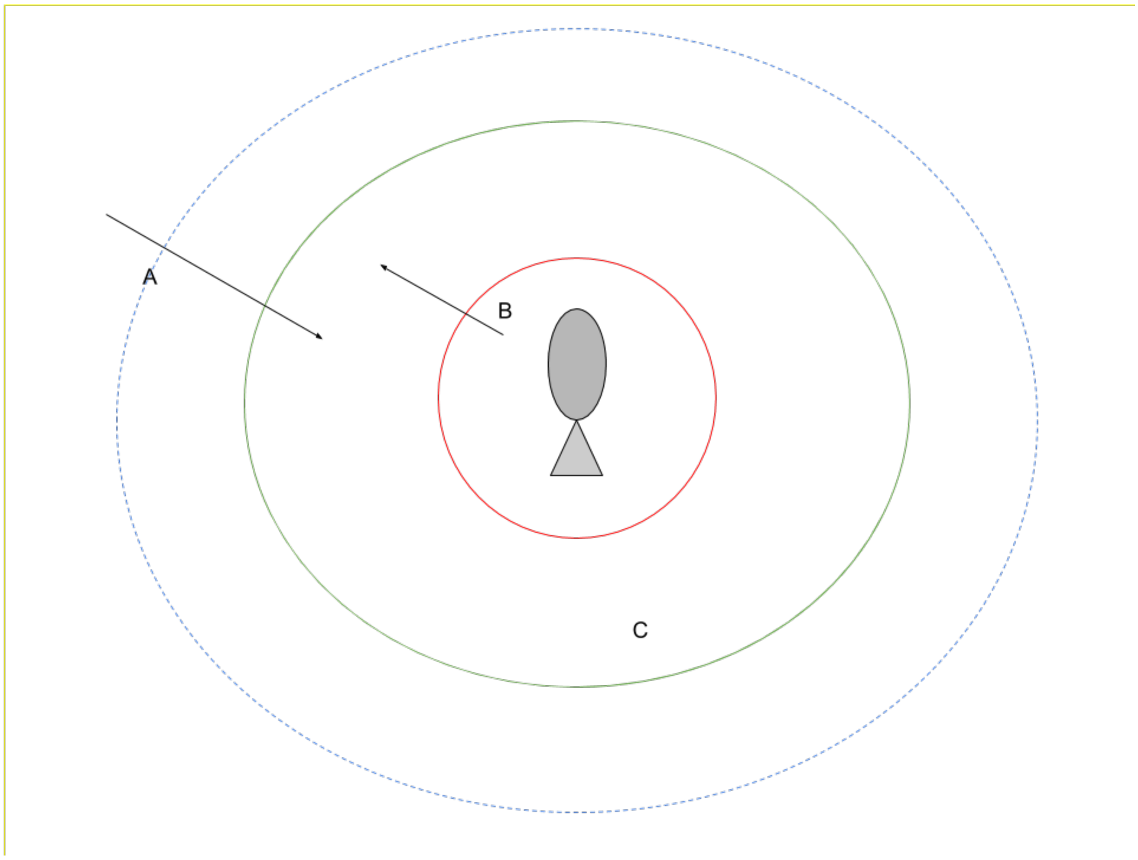

Figure 2: Conceptual overview of the zones. The center of all zones is the fish. The smallest zone, the rejection zone (red), defines the region in which no other individuals are allowed. The second largest zone which influence is around the rejection zone is the comfort zone (green) in which members of the swarm are preferred. The remaining outer region is covered by the attraction zone (yellow). Under certain circumstances, leading behavior gets triggered and the leading zone (dotted blue) is activated. A) If members of interest gain too much distance and enter the attraction zone, attempts are made to get them back into the comfort zone by approaching them. B) If rejection zone is entered, then there will be an attempt go gain distance to get the intruder back into the comfort zone. C) If the target of interest stays for a certain amount of time inside the comfort zone, the leading mode gets triggered and leading attempts are made.

As the guppies are around 2 to 3 cm long, initial reasonable values would lie around a radius of 8 to 12 cm. This is also supported by our tracking data which suggests that most fish will move in this periphery.

A too limited comfort zone would give the robot not enough space for taking its own actions as its comfort zone could be smaller then the comfort zone of the real fish. The robot is forced to always follow behind as the fish would far too easily drop out into the attraction zone with its movements. If the comfort zone is too large, the attraction zone would be too small or even non existing in the water tank. But then the robot would be always acting on its own and barely or never considering if the fish is actually interested in following it.

It is important to keep in mind that those extracted values are relevant for guppies. Other species will most likely have different preferences considering their deviating body structures.

The first theory was that a fish with a small comfort zone tends to follow other fish as it has less space to act until the other fish are entering the attraction zone which forces the fish to lessen the distance to get them back into its small comfort zone.

Analogously, a fish with a large comfort zone should be able to lead other fish as it can travel farther distances than the others. As the other fish would have the fish with the large comfort zone in their attraction zone while for first the others are still located in his comfort zone.

The behavior pattern of the module when activated is as follows. The algorithm will check for the closest fish to the robot with the nearest neighbor approach and choose it as its target. The robot will directly approach a customized focal point around the target fish in order to recruit it as a member of its swarm. The robot then being in the comfort zone of the fish will switch its role to the leader and move away by selecting random focal points in a cone in front of the robot in each frame.

If the fish follows it will stay in the comfort zone of the robot which means that the robot can continue to randomly move around the tank. If the fish does not follow it will leave the comfort zone of the robot. Then it forces the robot to switch back into an approaching-following behavior to try to recruit the target fish once again.

After implementation of the first version the resulting interaction between robot and fish did not look very promising at all. There were two cases:

A Now and then the fish even seemed to fear the robot. This was indicated by speeding up and getting a higher distance to the robot which excelled the rejection zone by far. Usually they would try to stay in attraction zone, indicating that robot and fish did not form a swarm at all.

B In other cases the fish did not mind the robot at all, swimming its own route, never seeming to care if the robot was close or not. It did neither react to approaches nor leading attempts.

From this following possible problems can be deduced:

1. The robot is driving too fast and is scaring the fish

2. Usually the robot approaching from behind due to constant movement of the fish. The robot might not be well percepted due to the restricted field of view which caused no reaction at all or feared the surprised target when it finally noticed the robot.
3. The fish may not see the robot as swarm member but more as an unknown individual. To build up some kind of relationship they needed to spend more time together while in each others comfort zone.

To recruit the fish a small comfort zone would be preferable to get the needed quality time. But for leading a bigger comfort zone is needed. This leads to the idea of either a flexible comfort zone which size depends on situation and current desired behavior (following or leading) or rather an additional bigger leading zone which will inactive the comfort zone when leading behavior is in action while the comfort zone stays smaller and is merely used for approaching and following purposes.

To get the target fish used to the robot, a time parameter called dwell time was introduced to force the robot to follow the target for a certain amount of seconds before trying an attempt to lead by getting more distance to the target fish. It serves as a count down which is reset if the target enters the attraction zone.

Both, leading zone and dwell time, do not exist in Couzin's original model but without them successful leading behavior was not possible to trigger.

Another important aspect is also the way of movement from the robot. Driving a long straight line seems less attractive then just going small steps forward and after every step changing the angle a little. With the latter strategy the movements of the robot look more similar to the natural stop and go movement of real guppies. This was not considered at all in Couzin's model as it was tested as computer simulation as proof of concept in which real natural movement would be negligible.

The whole code is implemented as a behavior class inside the framework. It's most important dependencies are the FishTracker and the motor controller.

The behavior can only show reasonable behavior if the FishTracker can give correct tracking information. Getting the wrong positions will cause confusion in every step of the algorithm as the distance between fish and robot is evaluated in every single frame. Even if the FishTracker may not work for a short amount of time e.g. due to connection issues it will instantly cause a malfunctioning behavior in the robot. In turn the fish will also be inappropriately influenced or even scared in the process which could distort all follow up interaction after the fix.

Even if there is a tracking mistake in a single frame, it will lead to the robot unnecessary switching to wrong following behavior as positions are evaluated relative to the zones and with them being hard coded borders are checked every frame. There exists no tolerance yet which might soften single tracking mistakes.

The controller of the motor also needs careful fine tuning. The forward speed of the robot cannot be too fast as it would frighten the fish or in worst case even collide with it. Even the fish does not show fear and is willing to follow, a too fast robot would leave the fish behind. Hence it would

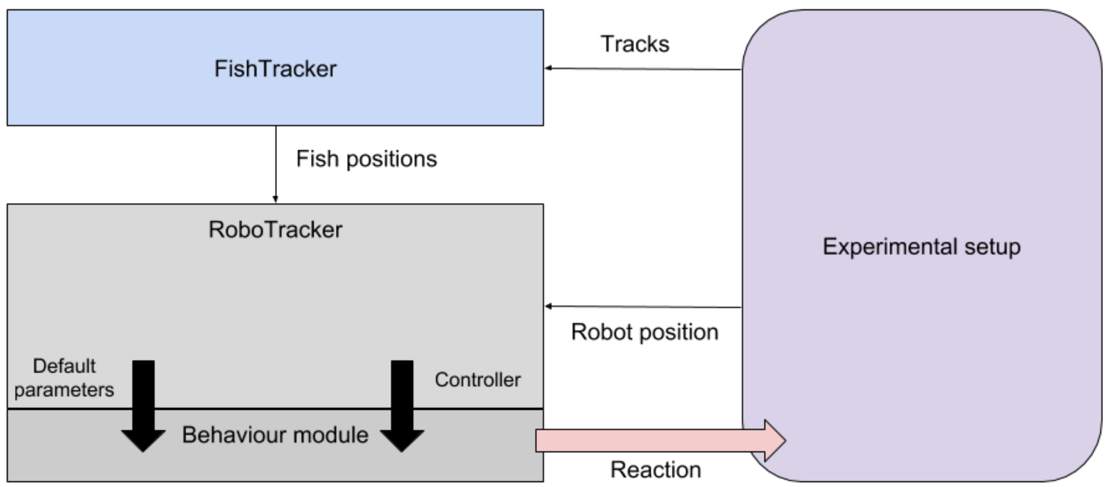

Figure 3: Conceptual overview of system dependencies. The behavior module needs both the positions of the fish and the robot in the water tank provided by the visual camera data and the image processing in FishTracker and RoboTracker. As both software components are currently located on different computers, a stable wireless connection is necessary. Parameters can be manually customized in the GUI of the RoboTracker. Those values can only also be changed during the behavior modules execution.The motor controller managed by RoboTracker needs to be carefully tuned. The forward and turning speeds need a certain range to be attractive for the fish. As the algorithm will then evaluate the positions and its consequences in the executed behavior, it feeds back its reaction to the real world.

leave the leading zone and the robot would wrongly assume that the fish is not following and turns around again to approach even if the fish actually wants to follow.
On the other hand if the robot is too slow, it might be always trapped in following mode as during the dwell time count down it cannot stay close enough to the target fish.
As the basic logic is rather simple, additional sub behavior types can easily be added by new functions which are called on specific conditions. For example a controller module was added to specify which focal point around the target the robot will move to. This can enable experiments whether there are differences if the robot is approaching from different sides or if it stay in the front or of the back of the fish and also allows to keep different distances to the target inside the comfort zone.

4.2 Experimental setup

As a general proof of concept and to do a first fine tuning of the parameter set of the implemented model, 30 trials with real fish were taken. As the amount of available fish was not higher during this works creation, those first results rely on rather few data points. This could be improved in future works when more fish are available for testing to fine tune the system further.
To keep the parameter space small for the low amount of possible trials, two core parameters were considered to be tuned during the trials: dwell time near target fish before leading behavior gets triggered and comfort zone.
The rejection zone was fixed at 3 cm, as it was already mentioned before that guppies usually keep that amount of distance between each other. The leading zone got a high value of 40 cm. Our tracking data suggests that most fish will never swim farther away and usually they also stay closer to each other. Therefore 40 cm seemed a reasonable value to fix the leading zone to ensure that the target fish will always stay inside leading zone if it is indeed following the robot even if it may move a bit slower.
For three trials the two interchangeable parameters were fixed and after every third trial just one parameter got slightly changed to slowly explore the parameter space. The chances of all three cases showing poor leading results even if the parameters are in reality well chosen should be low enough to get a reasonable idea about the effects of dwell time and comfort zone on the system.
Additionally three outlier trials were taken but their parameter values were just tested once. Theoretically they should show low amount of successful leading as in concept their values should be suboptimal.
The values of interest for the parameter sets to sample were:

- Dwell time: 0, 2, 3 seconds, with an outlier trial of 10 seconds
- Comfort zone: 10, 12, 15 cm, with outlier trials of 5, 30 cm

Per trial one fish was placed in the same tank as the robot. In the beginning of each trial, the fish was placed in a non transparent cylinder for 5 minutes to calm down. Afterwards the cylinder was opened. In front of the opening the robot was waiting. It was up to the fish to decide when to

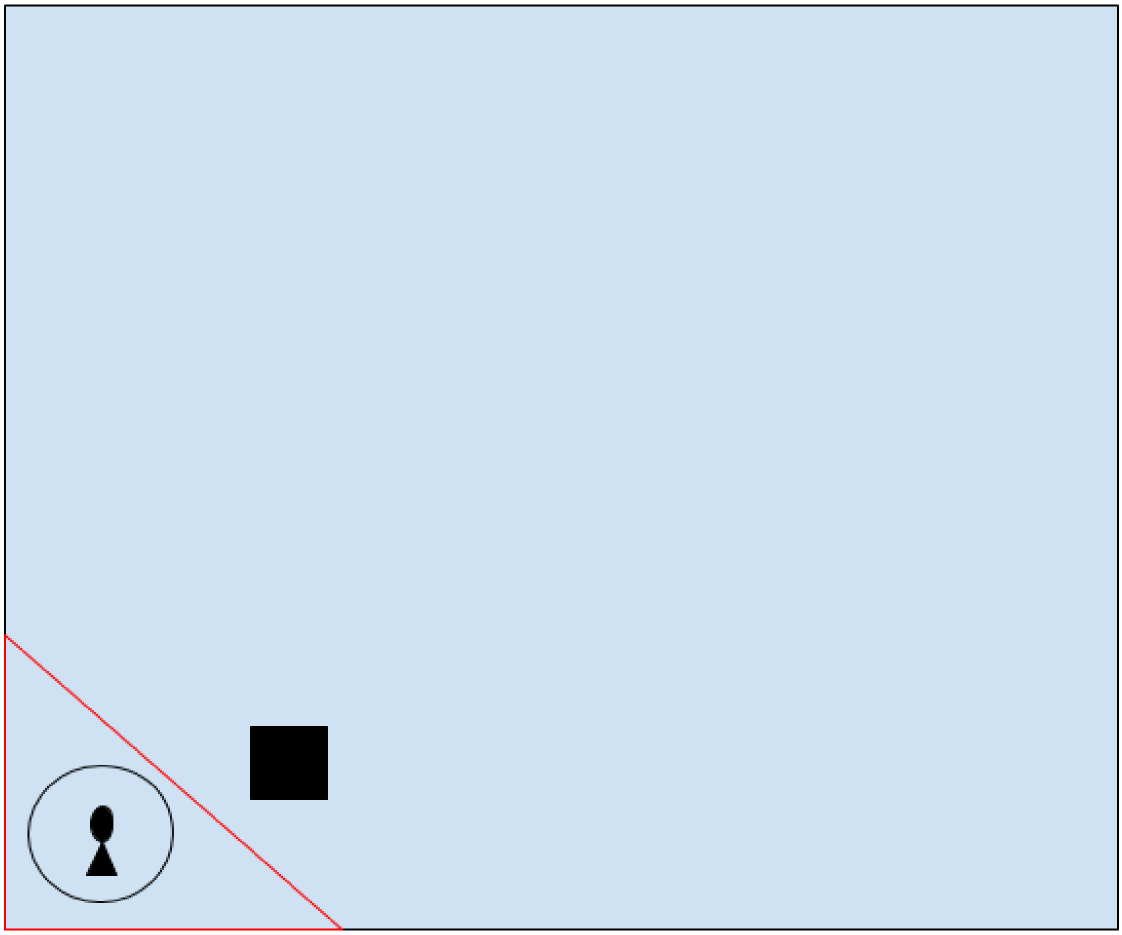

Figure 4: The experimental setup. A non transparent cylinder is placed in the lower left corner of the water tank, represented by a cycle. The fish resides inside the cylinder for 5 minutes before the opening directed to the robot (represented as a black square) gets cleared. To ensure a smooth procedure, the robot, usually allowed to travel the whole space of the tank, is not allowed to enter the region inside the red triangle. The rest of the tank is freely usable by the robot without any restriction besides the algorithms rules.

leave the cylinder and start the behavior of the robot which was activated by the user manually the instance the fish could be seen on the camera from above. The behavior would be played without any further exterior influence for 10 minutes straight. Every trial was recorded and tracked. The tracking contains the information of the absolute position and angle of both the robot and fish in the tank, the zone in which the fish currently is and the type of behavior the robot is executing depending on the fish position relative to the zone saved in csv files.

5 Evaluation

The results of the trials can be best analyzed by looking at the absolute distances between robot and fish over time. If plotted in a time series, the data gets visualized like a very spiked curve. This lies in the nature of recruiting the fish by traveling distances in the range of the leading zone, in this cases 40 cm, as well as the natural stop and go movement of guppies. As we also know the exact behavior of the robot, the curve can be color coded with the current behavior, red for following and green for leading.

As the robot starts the leading behavior, it does not automatically result into the fish successfully being recruited and following. In this cases there is a typical pattern: The robot drives back and forth between the fish and randomly chosen positions is farther distance. In this cases the attempted leading has a rather short duration limited by the leading zone size and can be easily filtered out. Those will be then categorized as failed leading attempt, marked as yellow.

To also be able to quantify the amount of executed behavior type depended on the euclidean distance between fish and robot, the same data is visualized in a histogram. Intuitively, the leading mode should occur more often in lower distances. The get an idea in which distance the following fish prefers to dwell, the median of all data points during leading mode is computed.

Following will be triggered in high distances and should accumulate there. But as following is also activated until the robot reaches the fish and stays in its neighborhood for the amount of dwell time in can also accumulate in lower distances, especially if the dwell time has a higher value.

The trials with the highest amount of green for leading behavior should give back an idea for optimal parameters for the algorithm.

An overview of the results can be found in Table 1.

The trials show mixed results. Ranging from fish following not at all to following almost all the time. Even inside a set of three trial which share exactly the same parameter values, results can be quite different. This can be explained due to individual character traits of fish and their current mood as the implemented model is not able to consider these criteria.

It can also happen that a fish attempts to explore its surroundings, hereby distance itself from the robot. But it still intends to follow and would soon return into close proximity to the robot. This case can also not be recognized when the fish accidentally leaves the leading zone in that process. The robot would assume a change of mind from the fish and instantly switches its behavior which would count as an inaccurate reaction.

To show the typical pattern of the behavior with different amount of successful leading time, three cases will be presented in the following.

Table 1: Numerical results of all trials.

Trial	Leading percentage	Comfort zone	Dwell time
26	81.7324	0	10
27	37.1789	0	10
28	27.9991	0	10
29	40.0359	2	10
30	56.6671	2	10
31	10.5586	2	10
32	30.6818	3	10
33	22.8985	3	10
34	64.2274	3	10
35	34.4212	0	15
36	81.7473	0	15
37	66.1231	0	15
38	32.5321	2	15
39	96.8644	2	15
40	98.6132	2	15
41	39.0395	3	15
42	0	3	15
43	2.96852	3	15
44	71.0347	0	12
45	0	0	12
46	72.3336	0	12
47	16.786	2	12
48	70.1586	2	12
49	33.8081	2	12
50	44.3408	3	12
51	46.5778	3	12
52	38.4453	2	30
53	0	2	5
54	2.78188	10	12
55	61.3939	1	30

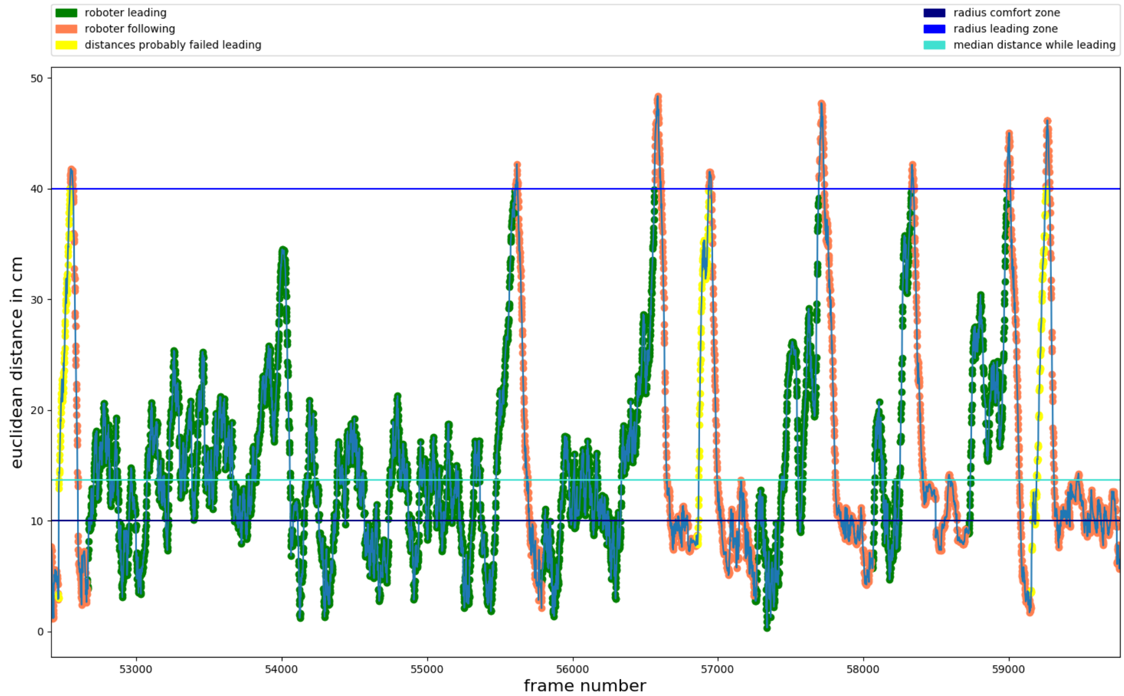

Figure 5: Time series for trial 34 with around 64 % of time leading. Dwell time: 3 seconds. Comfort zone: 10 cm

In the first case a mix of leading and following can be seen. For around 60 % of the trials time, the robot was able to successfully lead the fish. In Figure 5, the length of leading episodes though decreases over time. During the last third, it needs to recruit the fish several times again until it is only able to follow the fish during the very last period. As the leading times are getting shorter after each recruitment, this might indicate that the fish loses interest over time.

Figure 6 suggest that the observed distances of the fish to the robot accumulate more around the computed mean value of all distance while leading (around 14 cm) and reminds of a noisy normal distribution. It is worth to notice that the following behavior has two local maxima. One around the comfort zone radius, the other around the leading zone radius. This proofs that the zones have indeed an influence on behavior change as it is assumed by the model. The low occurrences of failed leading are neglect able as it had no big influence on the fish's reaction during the overall trial.

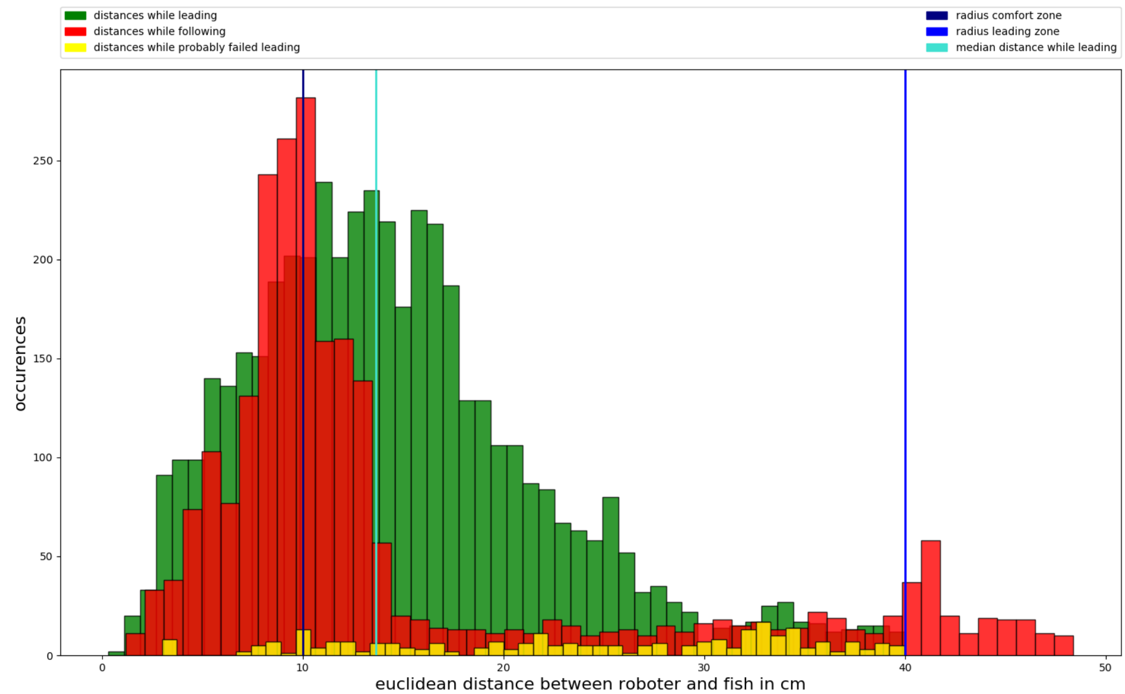

Figure 6: Histogram for trial 34 with around 64 % of time leading. Dwell time: 3 seconds. Comfort zone: 10 cm

In the following case the robot managed to recruit the fish once in the beginning and lead it for the whole remaining time of the trial for approximately 97 % of the time. The main change is a larger comfort zone of 15 cm which is 5 cm more than in the last trial. The larger space means more freedom for its own actions and less complications during recruitment as dropping out into the attraction zone is more difficult. (Figure 7)
Here the mean distance value during leading is ca. 12 cm. This can be explained by having only one recruitment scenario in the very beginning. As higher distances naturally accumulate during recruitment attempts, lower amount of recruitment attempts lead to less longer distances in which the fish needs to catch up with the robot first at the start of a leading procedure.(Figure 8)
It is interesting to note that for some cases with a leading time of over 90 %, the fish tend to stay next to the robot even after the trial was over and there was zero movement going on from the dummy fish.

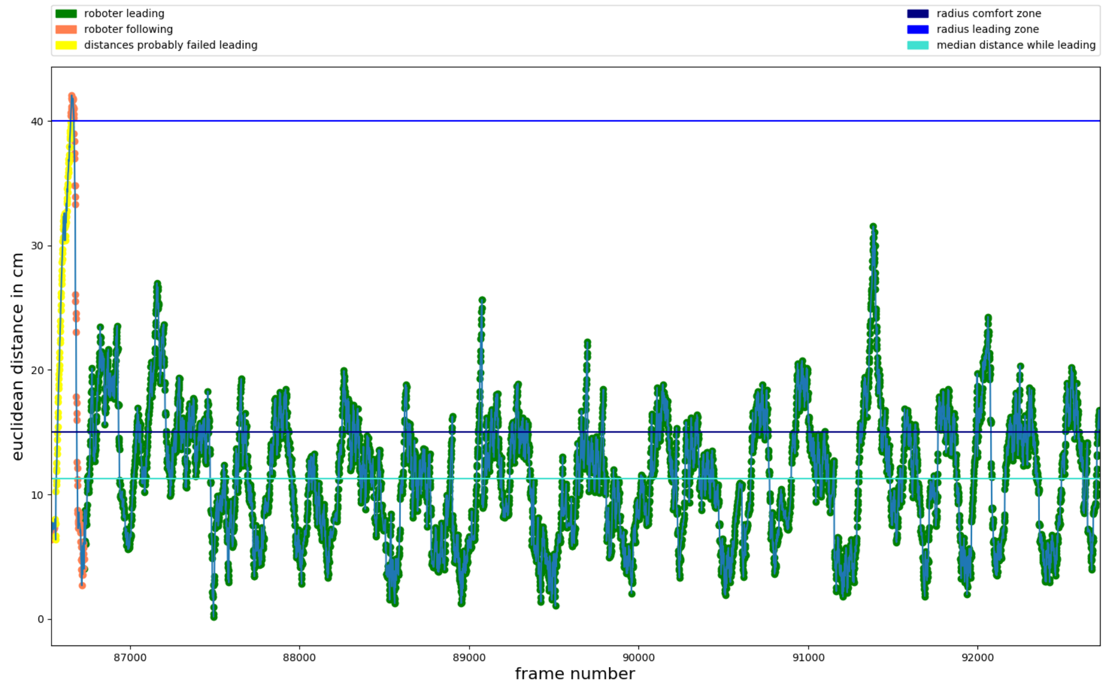

Figure 7: Time series for trial 39 with 96.86 % of time leading. Dwell time: 2 seconds. Comfort zone: 15 cm.

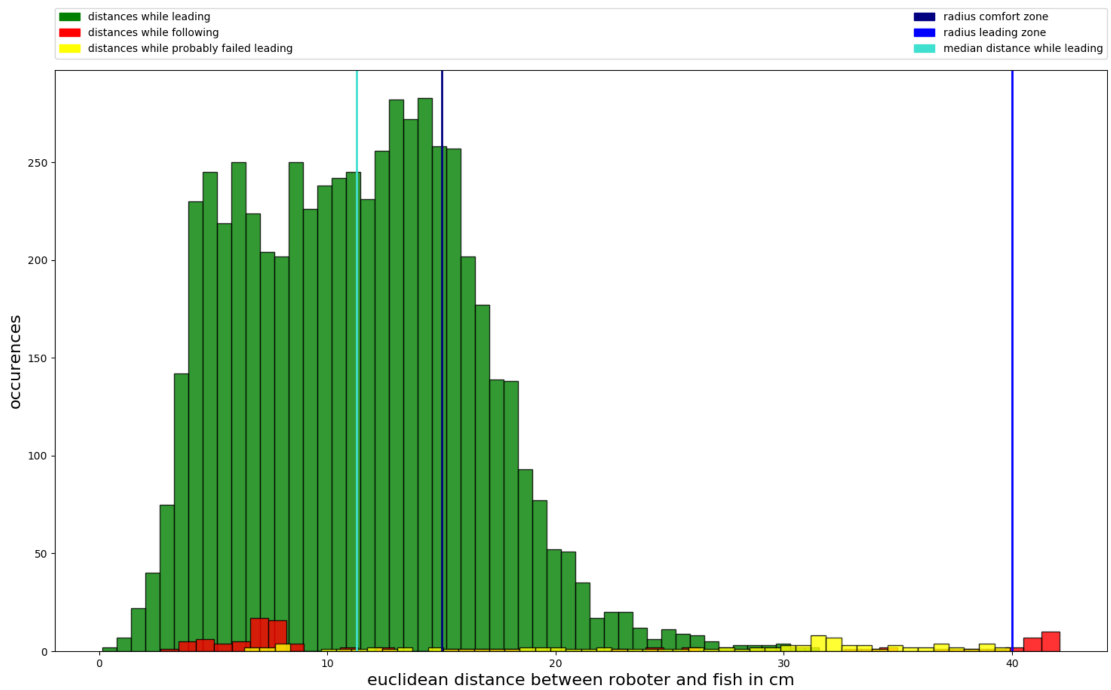

Figure 8: Histogram for trial 39 with 96.86 % of time leading. Dwell time: 2 seconds. Comfort zone: 15 cm.

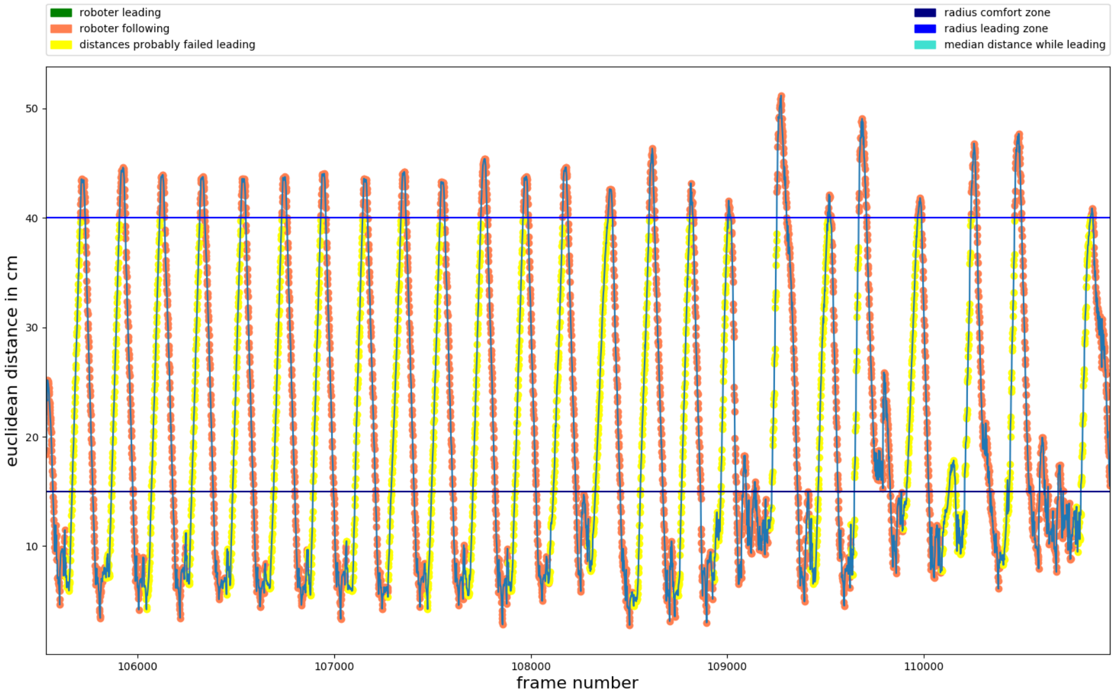

Figure 9: Time series of trial 42 with 0 % leading time. Dwell time: 3 seconds. Comfort zone: 15 cm

In the final case, the robot was never able to successfully recruit the fish, see Figure 9. Therefore it is only a series of going back and forth without any real interaction. There are zero occurrences of successful leading.(Figure 10) The comfort zone has a size of 15 cm as well but the difference to the previous case is the dwell time which is here one second longer. The rather small change in the time setting could actually be a strong influence in the system. Trials with the parameter set of 2 seconds dwell time and 15 cm comfort zone show promising results in regard to successful leading while trials with the same size in comfort zone but 3 seconds in dwell time show overall undesirable results in the leading category.

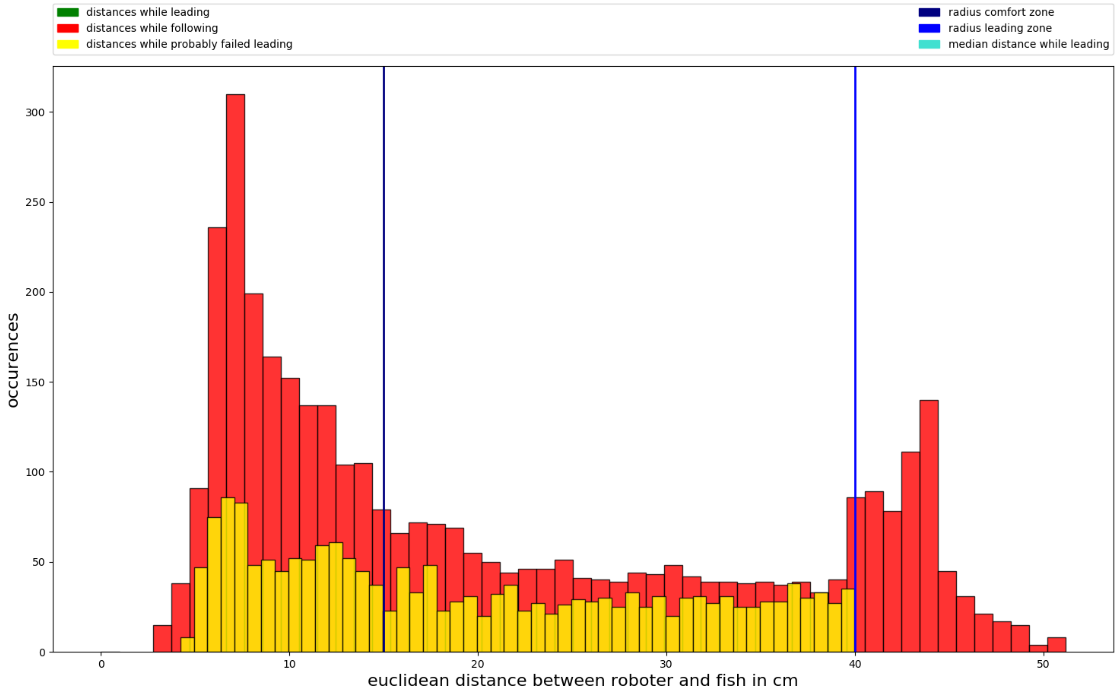

Figure 10: Histogram of trial 42 with 0 % leading time. Dwell time: 3 seconds. Comfort zone: 15 cm.

To find a qualitative description of the leading ability of the robot for each tested parameter set, the percentage of time in leading during one trial was computed by

$$\frac{\text{\# of frame during leading mode}}{\text{\# of all frames}}$$

Except for the outlier trials, for each parameter set the corresponding three trials the mean value of their percentage values in leading were taken and named the proportion of time in leading mode. Those proportions results are summarized in Figure 11.

The contour plot shows only a small region marked with high leading proportion. Larger comfort zones seem to be more favorable overall though its peak values lies around 15 cm.

On the other side, dwell time should stay low, as values above 2 seconds let the leading percentage drop quickly. But 0 seconds look as well not promising. This confirms that the fish needs a small accustom time before it accepts the robot as a swarm member. But if it takes too long, the fish seems to take on the role of the leader.

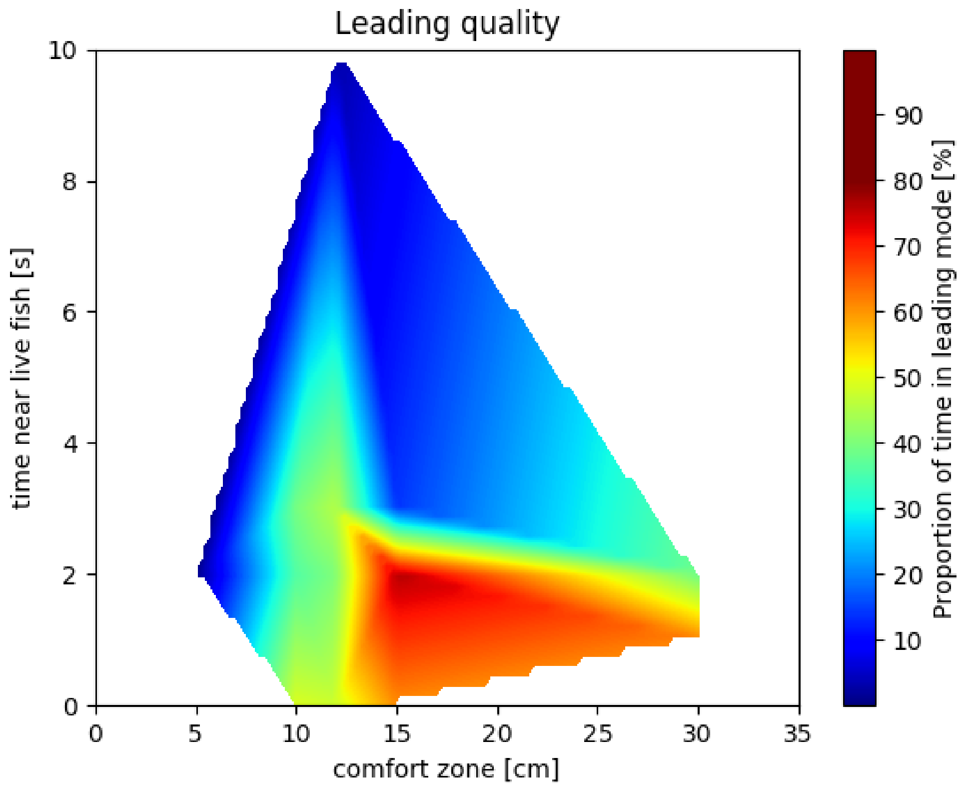

Figure 11: Sampled parameter space of leading quality. Considering comfort zone and dwell time as tunable parameters. The remaining aspects stay fixed. A high proportion of time during active leading mode is considered good leading quality for a leader. Low proportions indicate a follower. As high proportion can only be achieved in a small area, the robot seems to need rather specific characteristics to qualify as a leader. A comfort zone of 15 cm and a dwell time of 2 seconds are therefor proposed as optimal parameter values.

6 Discussion

6.1 Current state

The experiments investigated the parameter space of the zone model but restricted itself to two core parameters for fine tuning as the possible amount of trials was rather low. The results for all trials are quite different and show that there is only a small optimum in space which leads to high amount of leading. In general with some adoptions, the zone model used by Couzin in computer simulations, is successfully applied for leading behavior in wet lab experiments with real inter actors.

Interestingly the first assumption that the comfort zone should be around 8 to 12 cm large as this equals the three to four times of the body length of the guppies seems not quite accurate. As in Figure 11, the amount of leading is lower in that region but instantly improves with larger comfort zones. As the size of the comfort zone indirectly also influences the start of the dwell time counter, a small comfort zone may keep the robot close to the target fish for too long. As it can already be seen that long dwell times lead to a fast drop in leading quality, similar is applicable to a small comfort zone.

As unfortunately only 30 fish were available during this works progress, it is recommended to do more trials in the future for better statistical accuracy. Working together with animals gives the additional problem that they are not always willing to cooperate which has an additional influence in the data that needs to be taken into account. Also sampling more points in the parameter space may give unexpected results like a second optimum.

Also the model does not take into account the individual character traits of fish yet. Some of them are more bold, others are rather easily scared. Hence, different fish have diverging preferences. A bold fish might need another recruiting strategy than a shy one so that it can be led successfully. It can be assumed that bold fish are more complicated to be recruited as they will have a larger comfort zone and therefore can explore the space more freely according to the zone theory. Also they might dominant behavior which could hinder leading attempts.

Another factor is the cylinder in the setup which functions as an initial cover. Nakayama et al did a study examining different character traits and their willingness to leave the protective cover.[30] This was done with real fish in groups of three. It turned out that shy fish are readily leaving the cover when they see their partners outside. This tendency is not so strong in bold fish.

The tested setup in this work had a similar situation in the beginning of each trial. The fish inside the cylinder can see the robot through the opening. Different fish took a varying amount of time before they decided to leave the cylinder. In fact in some trial they were almost unwilling to leave the cover. It could be interesting to pursue this aspect in future experiments.

Shy fish should have a rather small comfort zone and will want to stay close to other swarm members for protection and are easier to lead. A possible issue could be that a shy fish gets more easily scared by an approaching robot. A flexible change in the robots forward speed to either keep up with a bravely exploring fish or carefully drawing near a shy fish with slow speed might

be another parameter worth to be implemented in the future.
Usually the guppies explore the whole water tank in the beginning when they are put inside. After their exploration ended they prefer to swim along the border walls of the water tank in cycles. The wall may give the fish some kind of protected feeling as in the middle of the tank they would be out in the open and easy prey for predators. It is worth to consider this factor as leading a fish into the middle could be more difficult due to the natural instinct of hiding from danger than leading a fish along the wall. Additionally pure position data along the wall are not purely distinct any more. The fish might fall in a routine after a while and is not really following the robot but instead merely taking the same route by chance. Those cases can be verified by changing to a more higher angle of new direction that would leave the protective area of the wall. In that sense, the distribution of the guppies positions is similar to that of zebrafish in a study of Collignon et al.[31]
As the whole data only analyses the interaction between the robot and a single fish right now, a possible next step would be the analysis with several fishes as new questions approaches with that problematic mainly about choosing the target. In its current state, the system only considers the nearest neighbor. This assumption might not always hold true in a larger swarm and should be investigated. In fact there are several possibilities: The robot considers all member of the shoal which must be kept inside the comfort zone or it chooses a nearest neighbor which is kept close to it. Even though this model is zone based it does not eliminate the fact that there could be also a topological factor that chooses the members that are desired to be kept inside the comfort zone similar to the studies made considering birds.[32, 33]

6.2 Outlook

For future work, different sizes of leading zone should give back the most interesting information about the system.
Due to the fairly simplistic nature of the zone model, there are a lot of possibilities to expand the models with further details to gain a more natural behavior. As could be seen in this works results, the model already shows promising data with few parameters in consideration. Step by step new features could be added that are deemed to be important and then tested in wet lab whether there is a positive improvement seen on the fish's behavior.
As an example, the position of the robot relative to the eyes of the target fish could be taken into account as the robot will not be well visible from all possible angles around the target as they eye is not able to perceive a whole 360 degree radius.[34] The consideration of the restricted field of vision was investigated in another work written in the Biorobotics Lab.[26]
Also as the model is not specialized on a specific research question, it can be easily adapted to new experimental settings in the future.
Nonetheless the zone models most disadvantage is its static nature by design. Even if it is extended by additional rules and parameters, the values are always fixed to certain values which are the optimal values in the parameter space in the best case scenario. But this defies the flexible nature of the real world in which there are too many factors and situations to be dealt with to handle

each of them in a new variable or special feature.

But the model is useful to derive a lot of important and informative data that can describe basic interaction. This data then could later be fed to a flexible system e.g. a machine learning module which has the ability to adjust flexibly to the individual behavior of its swarm member as well as specific environmental factors.

First ideas for a machine learning approach actually already exist, e.g training a Long Short Term Memory Networks (LSTM) and train it with fish trajectories.[35]

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