

RoboFish: increased acceptance of interactive robotic fish with realistic eyes and natural motion patterns by live Trinidadian guppies

This content has been downloaded from IOPscience. Please scroll down to see the full text.

2016 Bioinspir. Biomim. 11 015001

(<http://iopscience.iop.org/1748-3190/11/1/015001>)

View [the table of contents for this issue](#), or go to the [journal homepage](#) for more

Download details:

IP Address: 160.45.112.160

This content was downloaded on 12/10/2016 at 11:34

Please note that [terms and conditions apply](#).

You may also be interested in:

[Zebrafish response to 3D printed shoals of conspecifics: the effect of body size](#)

Tiziana Bartolini, Violet Mwaffo, Ashleigh Showler et al.

[Collective responses of a large mackerel school depend on the size and speed of a robotic fish but not on tail motion](#)

Maarja Kruusmaa, Guillaume Rieucau, José Carlos Castillo Montoya et al.

[Animal-to-robot social attachment: initial requisites in a gallinaceous bird](#)

L Jolly, F Pittet, J-P Caudal et al.

[Fish and robot dancing together: bluefin killifish females respond differently to the courtship of a robot with varying color morphs](#)

P Phamduy, G Polverino, R C Fuller et al.

[Zebrafish response to robotic fish: preference experiments on isolated individuals and small shoals](#)

G Polverino, N Abaid, V Kopman et al.

[A novel distributed swarm control strategy based on coupled signal oscillators](#)

Manfred Hartbauer and Heiner Römer

Bioinspiration & Biomimetics



PAPER

RoboFish: increased acceptance of interactive robotic fish with realistic eyes and natural motion patterns by live Trinidadian guppies

Tim Landgraf¹, David Bierbach², Hai Nguyen², Nadine Muggelberg¹, Pawel Romanczuk^{2,3} and Jens Krause^{2,4}

¹ Freie Universität Berlin, FB Mathematik u. Informatik Arnimallee 7, 14195 Berlin, Germany

² Leibniz-Institute of Freshwater Ecology & Inland Fisheries Müggelseedamm 310, 12587 Berlin, Germany

³ Princeton University, Department of Ecology and Evolutionary Biology, 302 Guyot Hall, Princeton NJ 08544, USA

⁴ Humboldt University of Berlin, Faculty of Life Sciences, Thae Institute, Hinter d. Reinhardtstr. 8-18, Berlin, Germany

E-mail: tim.landgraf@fu-berlin.de

Keywords: robotic fish, collective behavior, biomimetics

Abstract

In recent years, simple biomimetic robots have been increasingly used in biological studies to investigate social behavior, for example collective movement. Nevertheless, a big challenge in developing biomimetic robots is the acceptance of the robotic agents by live animals. In this contribution, we describe our recent advances with regard to the acceptance of our biomimetic RoboFish by live Trinidadian guppies (*Poecilia reticulata*). We provide a detailed technical description of the RoboFish system and show the effect of different appearance, motion patterns and interaction modes on the acceptance of the artificial fish replica. Our results indicate that realistic eye dummies along with natural motion patterns significantly improve the acceptance level of the RoboFish. Through the interactive behaviors, our system can be adjusted to imitate different individual characteristics of live animals, which further increases the bandwidth of possible applications of our RoboFish for the study of animal behavior.

1. Introduction

The study of collective movement in animal groups often comprises theoretic modeling as well as the analysis of pure observational data (Couzin *et al* 2002, 2005, Herbert-Read *et al* 2013, Katz *et al* 2011). These approaches identified interaction rules that animals use to stay within a moving cohort (see Lopez *et al* 2012). However, live individuals can hardly be forced to change their behaviors as intended by the experimenter (Krause *et al* 2011). Hence, the proposed interaction models have not yet been tested empirically. A recent solution is to replace live individuals in a group by biomimetic robots (Webb 2000, Krause *et al* 2011, Butail *et al* 2015).

Experimenters can manipulate the robots' behavioral and/or phenotypical properties to investigate collective behavior. For example, Halloy *et al* (2007) developed a robot that interacted autonomously with live cockroaches and therefore allowed fine-scaled investigations of their aggregation behavior. In a study on bluefin killifish (*Lucania goodie*), Phamduy *et al* (2014) showed the effect of different coloration of

courting (robotic) males on female mating behavior. In a previous study, we showed that an interactive robot—the so-called RoboFish—was able to recruit live guppies (*Poecilia reticulata*) to the non-preferred center of the test tank (see Landgraf *et al* 2014).

A key prerequisite for the use of robots in the study of animal behavior is to develop systems towards which real animals react relatively naturally (Landgraf *et al* 2013, Bshary *et al* 2014). The robot should be accepted as a conspecific by live animals. Nico Tinbergen's (1948) idea of 'social releasers', meaning that only a small subset of perceivable cues are communicative signals, motivates the use of (minimalistic) robot models. Those cues are highly species-specific and animals often use sets of multiple cues to assess their (social) environment (i.e., Candolin 2003). The identification of relevant cues and their realistic imitation is one of the most challenging parts in developing biomimetic robots (Krause *et al* 2011). Here, we propose three levels on which relevant cues may have to be imitated: (1) constant cues, (2) open-loop dynamic cues, and (3) closed-loop dynamic cues. Constant cues include the visual appearance, scents, body

Table 1. List of recent studies using biomimetic robots in research on fish behavior. It shows the species investigated and the class of the applied robot control as well as the social context of the experiments.

Species	Study	Social interactions	Social context
sticklebacks	Faria <i>et al</i> 2010	open-loop	single
	Landgraf <i>et al</i> 2013	closed-loop	shoal
guppies	Landgraf <i>et al</i> 2014	closed-loop	shoal
	Abaid <i>et al</i> 2012	open-loop	single
	Butail <i>et al</i> 2013	open-loop	shoal
	Butail <i>et al</i> 2014a	closed-loop	single
	Cianca <i>et al</i> 2013	open-loop	single
zebrafish	Ladu <i>et al</i> 2015a	open-loop	single
	Ladu <i>et al</i> 2015b	open-loop	single
	Polverino and Porfiri 2013b	open-loop	shoal
	Polverino <i>et al</i> 2012	open-loop	shoal
	Spinello <i>et al</i> 2013	open-loop	single
	Polverino and Porfiri 2013a	open-loop	shoal
	Polverino and Porfiri 2013b	open-loop	shoal
mosquitofish	Polverino and Porfiri 2013b	open-loop	shoal
bluefin killifish	Phamduy <i>et al</i> 2014	open-loop	single
	Abaid <i>et al</i> 2013	open-loop	single
golden shiner	Polverino <i>et al</i> 2013	open-loop	single
	Swain <i>et al</i> 2012	closed-loop	shoal

temperature, tactile cues, etc—everything that, with respect to the sender, remains constant in time. In Halloy *et al* (2007), for example, the robot was treated with a cockroach-specific pheromone to facilitate group integration. Second, open-loop dynamic cues include predefined patterns of changes, like motions of the body or body parts, changes in body temperature or song playbacks. Third, closed-loop dynamic cues include all robotic actions produced as a function of the (social) environment.

The development of closed-loop systems is technically challenging since it involves (i) robust real-time identification and tracking both of robotic agents and live animals, and (ii) feedback control, as well as (iii) knowledge on species-specific social interactions.

Obviously, the complexity of a realistic robot model then varies with the sensory apparatus as well as the cognitive abilities of the target species (see Krause *et al* 2011). The challenge is first to identify relevant cues, then to implement realistic reproductions of those and finally to assess their effectiveness on the focal animals. In this regard, previous work found teleost fish to be a fruitful taxon as they do show sophisticated social behaviors (Brown *et al* 2011, Bshary *et al* 2014) and react relatively naturally towards dummies including robots (see table 1 for a list of studies focusing on robot-fish interactions).

In the present study, we describe our recent advances in developing a closed-loop biomimetic robot for the study of collective behavior in the guppy (*Poecilia reticulata*)—the *RoboFish*. First we describe our system's hardware and software components. Second, we report on recent improvements of constant, open-loop dynamic and closed-loop dynamic cues. Third, we evaluate the acceptance of the improved *RoboFish* in experiments with live guppies.

2. The *RoboFish* system

Our test arena consists of a squared glass tank (88 × 88 cm) that is filled to a level of 15 cm with aged tap water. The tank is placed on an aluminum rack at about 1.40 m above ground (figure 1(a)). Our system allows simultaneous operation of multiple robots. The two-wheeled differential drive robots move below the tank on a transparent platform (figure 1(b)). Each robot carries a neodymium magnet directed to the bottom side of the tank. A three-dimensional (3D)-printed fish replica (see section 3.2 for more details on the replicas) is attached to a magnetic base, which aligns with the robot. Hence the replica can be moved directly by the robot (figure 1(c)). On the ground, a camera is facing upwards to track the robots. A second camera is fixed above the tank to track both live fish and replicas. The entire system is enclosed in a black, opaque canvas to minimize exposure to external disturbances. The tank is illuminated from above with artificial light reproducing the daylight spectrum.

Two personal computers are used for system operation: one PC tracks the robots, receives swarm-tracking results from a second PC and computes and sends motion commands to each individual robot over a wireless channel. The second PC evaluates the video feed of the shoal camera, finds and tracks all relevant objects and sends those data to the first computer via a local area network connection.

2.1. Robot design

The two-wheeled robot is a cuboid with dimensions 7 × 7 × 10 cm built from aluminum and plastic plates (figure 1(a)). It houses three Arduino-compatible boards (so called 'shields') for main processing

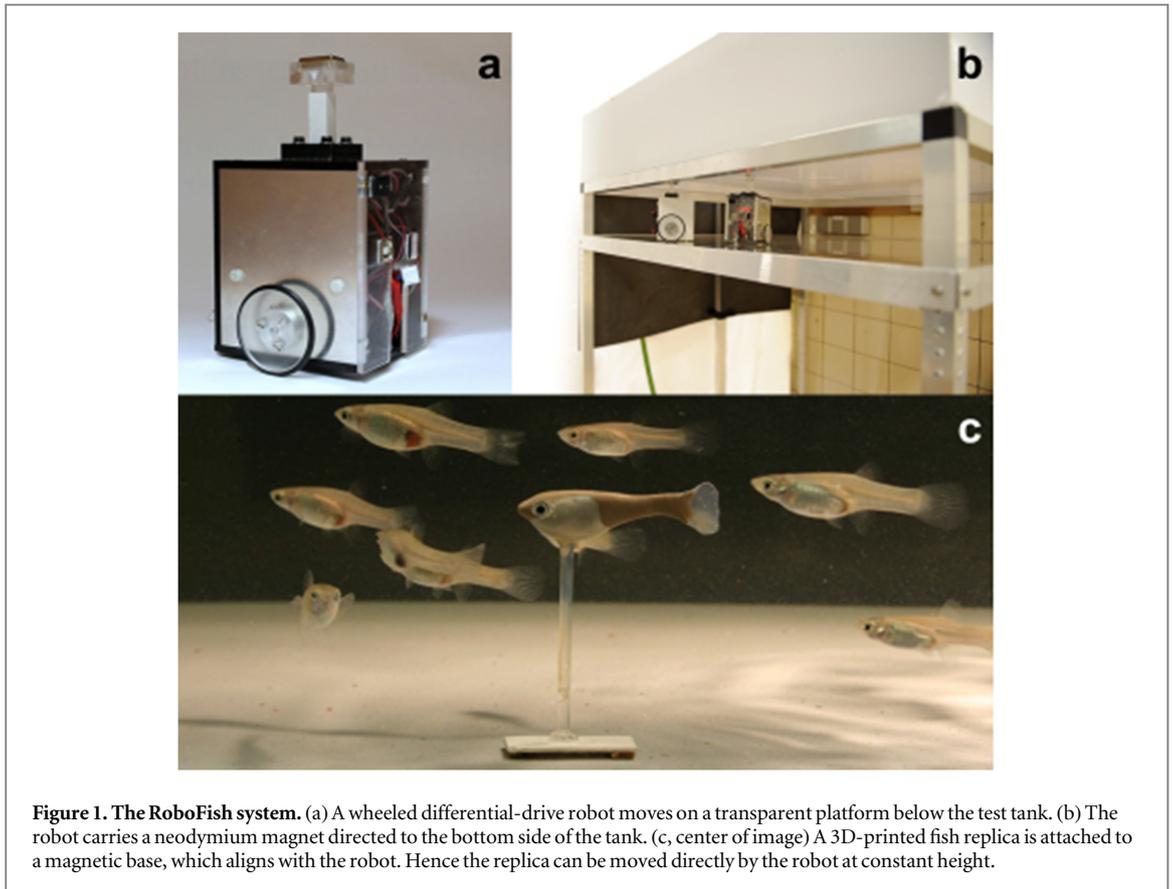


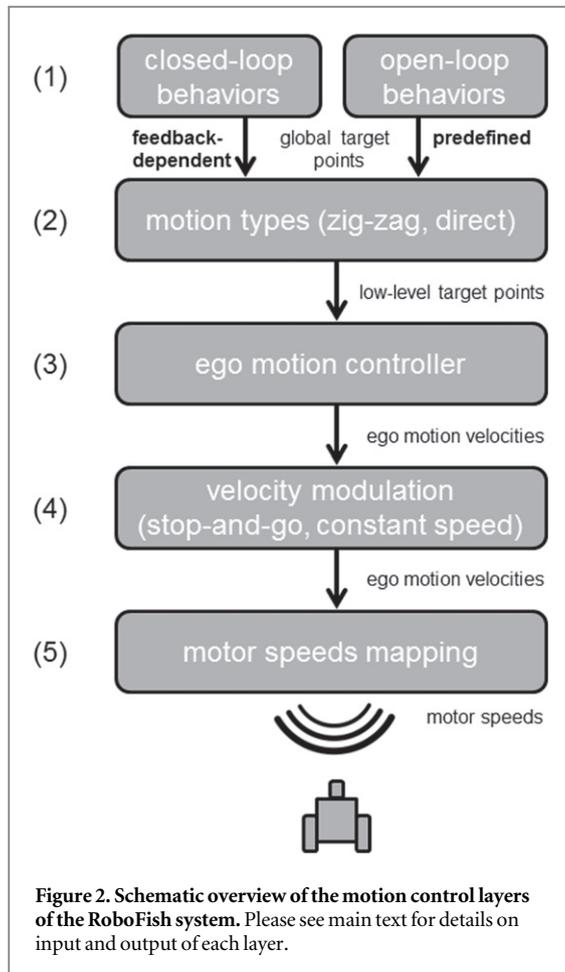
Figure 1. The RoboFish system. (a) A wheeled differential-drive robot moves on a transparent platform below the test tank. (b) The robot carries a neodymium magnet directed to the bottom side of the tank. (c, center of image) A 3D-printed fish replica is attached to a magnetic base, which aligns with the robot. Hence the replica can be moved directly by the robot at constant height.

(Arduino Uno, Arduino LLC), WiFi communication (Copperhead WifiShield, LinkSprite, Inc.) and motor control (DFRobot Motor Shield, DFRobot, Inc.). Custom-built wheels with rubber gasket rings are directly connected to two dc gear motors (2224U006SR 33:1 IE2-16, Dr Fritz Faulhaber GmbH & Co. KG). The main power is supplied by a LiPo battery pack (two-cell, 7.4 V nominal output, Conrad Electronic SE). The motors are driven via pulse width modulation (PWM) signals generated by the motor shield that relays a regulated voltage of 5 V (LM350T, Fairchild Semiconductor, Inc.). The regulator's output is fed to the Arduino main board as well. A voltage divider scales down the raw battery output, which then can be measured on an analog pin of the Arduino board with respect to an internal reference. Each robot carries a neodymium magnet at the tip of a plastic rod held up against the glass tank maintaining an air gap. The tank itself is made of glass, which due to the mass of the water column bends slightly downwards. The distance between the magnet and the tank therefore varies from less than 1 mm near the center of the tank to approximately 2 mm in the periphery. The magnets' poles are aligned in parallel to the motion plane and the replica's base aligns with the robot. This steady coupling allows on-the-spot rotations and fast accelerations of the replica.

2.2. Robot control and motion models

The control software sends motion commands at a frequency of 30 Hz, as determined by the bottom camera's frame rate. In each time step, a command packet is issued and sent to the individual robot via WiFi (UDP). Each robot has a unique IP-address and only receives its respective packets. We use a fixed length protocol with a 2 bytes header and 12 bytes data. The motion control is organized in five layers (see figure 2 for a schematic overview): (1) open-loop or closed-loop behaviors that generate global target points, (2) a layer that generates low-level target points according to preset motion types (linear or zig-zag motion), and (3) the translation to ego motion velocities taking into account the current pose of the robot and the current low-level target point, (4) an optional layer that modulates the ego motion velocities over time, and (5) a mapping layer translating ego motions to motor speeds. The output of the lowest layer is sent to the robots and is directly applied to the motors upon packet arrival.

The behavior layer (1) returns global target points, either from a predefined sequence of target points or as a function of the live fish positions (see section 3.3). The actual path from the current position to the global target is represented by a sequence of low-level target points as calculated by the motion type layer (2). When operating on a sequence of predefined global target



points this layer checks for every camera frame whether the current low-level target point has been reached (with a tolerance of 3 cm). If so, it returns the next low-level target point in the list. If the last low-level target point has been reached, the behavior layer (1) is notified. It then provides the next global target point in the list.

Layer (2) can be configured to produce a zig-zag or linear path. The zig-zag path is static for predefined behaviors and updated for every time step for closed-loop behaviors. The ego-motions, i.e., forward and turning velocities, are computed by the ego motion layer (3). These velocities follow sigmoid functions that depend on the Euclidean distance (forward velocity) and the angular deviation of the driving direction (turning velocity) to the low-level target point.

In the velocity modulation layer, ego-motions can be modified to match natural stop-and-go motion patterns. The forward velocities are multiplied by linear ramps that can be adjusted parametrically (see section 3.3.1).

The motors are able to propel the system to a maximum forward and turning velocity of approximately $60 \text{ cm}^{-\text{s}}$ and $860 \text{ deg}^{-\text{s}}$, respectively. The minimum velocities are approximately $1 \text{ cm}^{-\text{s}}$ and $15 \text{ deg}^{-\text{s}}$. Note that there is no low-level feedback control of

wheel turning velocities. The robots' motion is solely controlled via vision feedback.

Most of the computation is outsourced to personal computers. Currently, the robot's firmware implements the following: (1) Sending status packets back to the control computer at 1 Hz, including the robot's unique identifier and battery level. (2) Upon request, it toggles infrared light-emitting diodes (IR-LEDs) for the identification of the robot. (3) It generates PWM signals according to the received motor speed values. (4) It can be configured to run in jump-start mode. To overcome initial friction and inertia, this mode prepends higher PWM duty cycles when motor speeds are low.

Closed-loop behaviors use the continuous stream of sensory feedback from the fish tracking system. For each frame a transmission control protocol-packet containing individual positions is sent to the robot control computer. There, a callback routine is triggered to collect the data and to make it available in a data structure that represents the tank and all relevant objects, such as fishes and robots. We have defined a list of atomic behaviors that can be combined to a complex sequence. Atomic behaviors comprise, for example, 'following an individual with given identity (ID)', 'following the centroid of a shoal', 'alignment with individuals' (for more details see table 2). Atomic behaviors are available for both the open-loop and closed-loop behavior layer and can be adjusted parametrically. The closed-loop behavior layer logically connects atomic behaviors dependent on the current situation (real-time feedback). All closed-loop behavior modules exhibit a generic structure. They can access the current set of world information and produce a global target point that is passed to the lower layers of the planning hierarchy. For each robotic agent a different behavior can be defined. For example, one agent can be set to follow another robot for all times and this one can be configured to follow a live fish.

2.3. Computer vision

The RoboFish system uses two sensory channels: one for detecting and controlling specifically the robotic agents and the other to extract information on fish positions. As the major difference to systems with only one camera above the tank (proposed by Bonnet *et al* (2012) and Swain *et al* (2012)), this redundant setup ensures that robots do not get confused with live fish, a particular issue when observing larger numbers of individuals.

2.3.1. Robot tracking

We track the robots via their set of IR-LEDs in the base plates. The LEDs are aligned linearly, two in close proximity, at a distance of 3 mm. They designate the front of the robot. When operated on a transparent platform, each robot can be localized easily in the

Table 2. Atomic behaviors. The highest motion planning layers are composed of these predefined behaviors. Some atomic behaviors require real-time tracking information and thus are only available in closed-loop scenarios.

Atomic behavior	Modifier	Description	Open-loop
approach	nearest neighbor	global target point is set to the nearest fish or robot position	no
	neighbor X	global target point is set to the position of a given robot or fish	no
	shoal centroid	global target point is set to the centroid of the largest sub-shoal	no
	random ego-centric location	random target point relative to position and orientation of robot	yes
	random global location	random point drawn from predefined probability density over the tank	yes
align	tank location	a given tank location is used as the next global target point	
	nearest neighbor	body direction of nearest neighbor is matched	no
	neighbor X	body direction of given fish or robot is matched	no
	shoal	average body direction of individuals in shoal is matched	no
	point	turn robot to face a static point	yes
escape	nearest neighbor	move in opposite direction defined by relative nearest neighbor position vector	no
	neighbor X	move in opposite direction defined by relative position vector of a given fish or robot	no
	shoal centroid	move in opposite direction defined by relative position of shoal centroid	no
change	turning velocity	directly add or subtract values from current forward velocity	yes
	forward velocity	directly add or subtract values from current turning velocity	yes
wait		rest motionless on current position	yes

video feed of an IR-sensitive camera on the ground. For this task, we utilize a standard webcam (Logitech Pro 9000) with the IR-block cover glass replaced by an IR-pass filter. Hence, the IR-LEDs produce two very bright spots (one larger than the other) in the otherwise dark camera image. To localize the LEDs, a global threshold is applied to binarize the image. The result is then de-noised by an erosion operation (Serra 1983). Possible remaining gaps in the blobs are filled by applying a dilation operation (Serra 1983). Subsequently, we seek connected components (Wu *et al* 2009) that likely represent IR-LEDs. Since the distance of the LEDs on each robot is known, we can formulate a distance constraint for pairs of differently sized blobs in the image. These likely define the location and orientation of each robot. Robots that align antiparallel and run side by side might be perceived as two robots with perpendicular orientation. Thus, we additionally check whether the candidate blob pair obeys an additional smoothness constraint, i.e., given the current speed of movement, old and new blob location and orientation are sufficiently close. Before operating the robots, the program initially requests from all available robots to report their IDs. The unidentified virtual objects in the world model have to be assigned their respective correct ID manually. All image coordinates are rectified and translated to the world coordinate system using a user-defined rectangle that matches the arena's outline in the camera projection.

2.3.2. Fish tracking

Interactions of robots and live fish are observed from above the tank by a second camera. In order to detect all individuals, we use a background subtraction procedure that models foreground and background

pixel distributions as a mixture of Gaussians (Zivkovic and van der Heijden 2004). Since the tank's bottom and walls are laminated with white plastic, the fish appear as clear dark objects in the video images. Once converged, the background model shows an empty tank such that the difference image of background and current live frame exhibits distinct positive peaks. The individual fish are detected by first applying a global threshold to the difference image. All regions having above-threshold values are then treated similarly to the blobs in the robot tracking (erosion, dilation, connected component analysis—see section 2.2.1). Additionally, the blobs are assigned an orientation by integrating the motion vector over a fixed time window, when fast movements are detected. The system assigns an ID to every fish blob and tracks it using a simple model of fish motion (figure 3). For a given fish object, its motion speed in three dimensions (planar position and orientation) defines an expected position in consecutive frames. Since the number of fish in the tank is known and constant, we keep an according number of fish representatives and update their locations iteratively over time. Figure 3 depicts a sample shoal with overlaid tracking information. The shoal tracking system was validated in two regards: (1) the positional error of static objects was calculated by placing fish-sized metal blocks on known positions and comparing the system's output to the reference positions. The average error is below 1 mm (SD: 2 mm) but might be larger when objects are moving, or the polygon that defines the homography is set erroneously. (2) The tracking error was determined by counting the number of individuals that were either lost by the system or assigned the wrong ID (e.g., when fish are overlapping in the image). If an individual gets lost and found again, we would only count the loss.

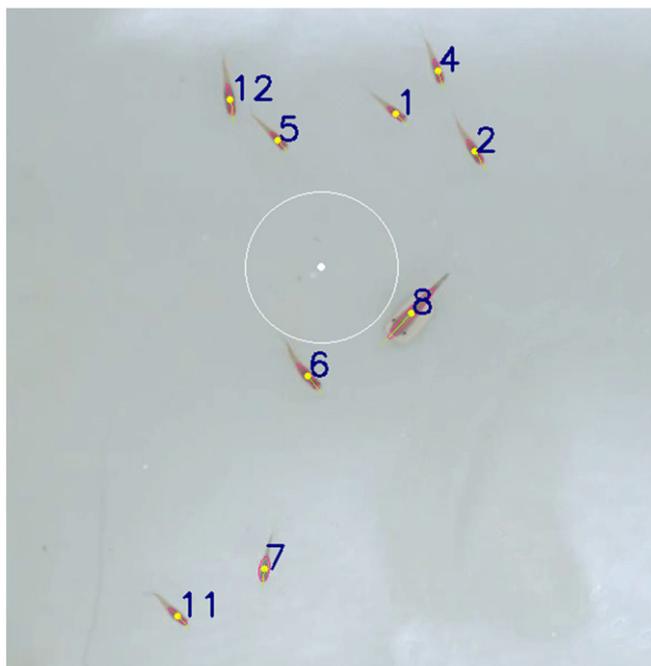


Figure 3. Screenshot of our fish tracking system with overlaid tracking information. Each fish exhibits an ID and an ellipse that reflects position and orientation. This data is sent to the robot control computer, which then clusters individuals and stores the center of mass (white dot with a circle whose radius is proportional to the planar variance = shoal size).

Five different video sequences of the same duration (1000 frames, 40 s) and varying numbers of individuals were subject to the tracker. On average, 1.2 errors per min occur—most of them produced in one sequence with many fishes overlapping.

2.3.3. Clustering

The fish tracking computer sends a list of fish positions to the robot control computer. Here, the positions are clustered to identify sub-shoals and their respective centroids. The clustering is a variant of the k-means algorithm (MacQueen 1967). We initialize the clustering with N cluster centers (with N being the total number of fish and robots in the tank) by assigning the i th fish (or robot) position to the position of the i th cluster center. Each cluster center uses a counter variable reflecting the number of fish that is represented. In a second initialization step, cluster centers are merged if both are closer than 5 body lengths (=15 cm). In that process, one cluster center is moved to the weighted average position. The weighting corresponds to the normalized counter variables. The new counter variable is updated by adding the counter value of the other cluster center, which is then removed from the list of cluster centers. The merging process is repeated until no cluster centers can be merged.

3. Improving RoboFish acceptance by live guppies

Regarding the previously described acceptance levels —(1) constant cues, (2) open-loop dynamic cues, and

(3) closed-loop dynamic cues—we propose that RoboFish should at least imitate (i) visual appearance, (ii) natural motion patterns, and (iii) close-range inter-individual distance (e.g., social interactions). The following section describes our work on all three proposed levels.

3.1. Test fish and their maintenance

Our test fish are descendants of wild-caught guppies (*Poecilia reticulata*) from the Caroni River system in North Trinidad and come from large, randomly outbred single-species stocks maintained at the animal care facilities at the Leibniz-Institute of Freshwater Ecology and Inland Fisheries (IGB) in Berlin. To avoid inbreeding, stocks are regularly supplemented with wild-caught animals brought back from fieldwork in Trinidad. Only adult animals were used for experimentation.

3.2. Constant cues: visual appearance

The fish replicas were 3D-printed standard models (figure 4(a), see Phamduy *et al* (2014) for a similar approach). The 3D mesh was produced manually from several template photographs (see figures 4(b), (c)). The printed replicas were then painted and finished (figures 4(a), (d), (e); see also Landgraf *et al* 2013) and equipped with glass eyes (figure 4(a); 3 mm diameter, model: kristall B11; Lauschaer Glasaugen, Frank Weigelt). We decided to create only replicas that resemble female guppies. Previous research showed that females were similarly preferred as shoaling partners by both sexes (Magurran 2005) while males

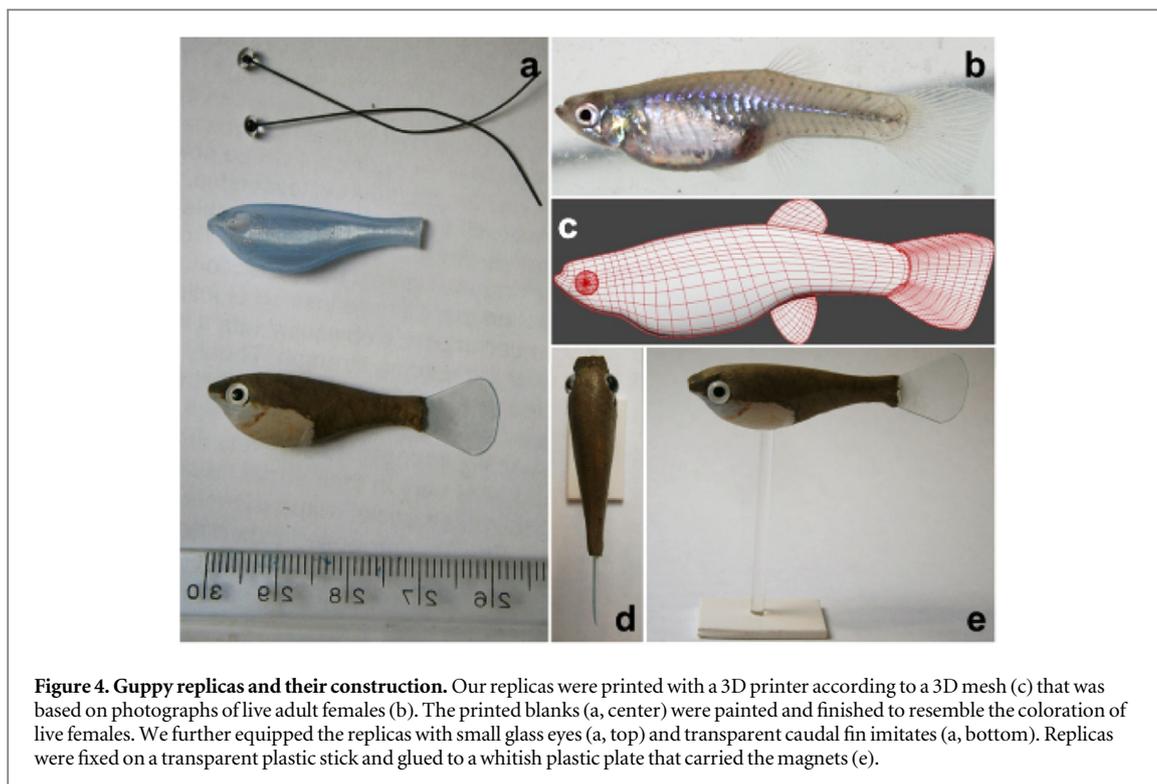


Figure 4. Guppy replicas and their construction. Our replicas were printed with a 3D printer according to a 3D mesh (c) that was based on photographs of live adult females (b). The printed blanks (a, center) were painted and finished to resemble the coloration of live females. We further equipped the replicas with small glass eyes (a, top) and transparent caudal fin imitates (a, bottom). Replicas were fixed on a transparent plastic stick and glued to a whitish plastic plate that carried the magnets (e).

are often avoided by females due to the typically high rates of male sexual harassment (see Magurran 2005). Female guppies prefer to associate with same-sized conspecifics. Therefore, our replicas are similar in size compared to live fish (mean body length of adult guppy females from our stocks range from 24.51 mm to 36.63 mm with a mean of 30.09 mm; $N = 36$ randomly selected adult females sampled; replica size is 30 mm, see figure 4(a); all measures represent standard length measured from snout to end of caudal peduncle).

3.3. Open-loop dynamic cues: natural motion patterns

In guppies, explorative swimming is characterized by an alternation of swimming phases (velocity > 0) and stop phases (velocity = 0) (see Mikheev and Andreev 1993). Often fish propel themselves with only a few tail beats and then glide through the water, eventually slowing down until they stop. The imitation of this pattern might improve the acceptance of the replica as a conspecific. To confirm this idea we analyzed the swimming performance of live guppy females and implemented the observed swimming characteristics into the motion repertoire of the RoboFish.

3.3.1. Tracking of live guppies' swimming performance

We separately introduced 16 females into an opaque plastic cylinder (diameter 5 cm) placed in the middle of a round standard open field arena (48 cm diameter, 5 cm water level). The smaller tank enabled an analysis with higher spatial resolution compared to recordings

in the RoboFish test tank. After 60 s of acclimation, the cylinder was removed and the movement of the female was videotaped for 3 min. Test fish were introduced to the arena one week prior to the recordings (1×5 min) and thus could familiarize with the environment. The test was repeated for each fish after one week, yielding 32 videos in total. We tracked all fish using our fish tracking software with a reduced sample rate of 10 Hz. Obtained coordinates were then smoothed (Savitzky–Golay, Polynomial-Order: 1, half-window: 5 samples = 0.5 s). Based on these observations we propose a model with four distinct motion phases (figure 5): The stop phase, the acceleration phase, the steady swimming phase and the deceleration phase. The stop is defined as a period with less than $2 \text{ cm}^{-\text{s}}$ forward velocity. Averaged over all animals, the median stop phase duration was 0.83 s. The acceleration phase is defined as a period with increasing velocity. On average, fish reached a maximum velocity of $5.7 \text{ cm}^{-\text{s}}$ over a time interval of 0.46 s. This acceleration phase was sometimes but not always followed by a steady swimming phase, which started after the first velocity peak (V_{max} at acceleration phase). If such a phase was present, median velocity oscillated around an average of $5.8 \text{ cm}^{-\text{s}}$ for an average median duration of 2.1 s. Note that velocities per definition never dropped below the stop phase threshold of $2.0 \text{ cm}^{-\text{s}}$. The following deceleration phase is defined as a period of continuously decreasing velocity (to below $2 \text{ cm}^{-\text{s}}$). We measured an average median deceleration phase duration of 0.52 s. Subsequently, the fish enters a new stop phase.

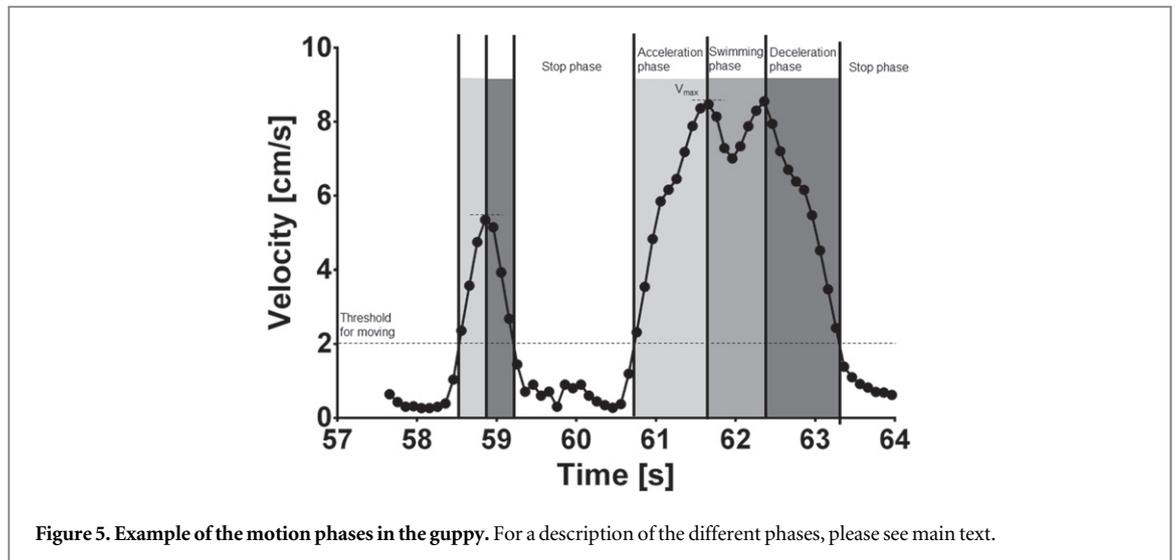


Figure 5. Example of the motion phases in the guppy. For a description of the different phases, please see main text.

3.3.2. Implementation of motion phases

We implemented the above described motion phases using five model parameters. The result is a sequence of linear ramps over time, which is multiplied with the forward velocities coming from motion planning layer 3 (the ego motion controller). The velocity of the robot is linearly increased over the *acceleration duration* until the *maximum velocity* is reached. Then, the robot is moved at constant speed over the *steady swimming duration* until it decelerates linearly to a full stop over the *deceleration duration*. The *stop duration* completes the set of model parameters. Our current robot does not use encoder motors. It is thus not possible to control wheel rotation velocity (and thereby forward velocity) in a low-level feedback loop. The size of the replica further affects the forward velocity for a given controller output. Therefore, when using different kind of replicas (e.g., for other species) each robot/replica combination has to be calibrated, i.e., the replica's forward velocity has to be measured over a number of PWM values.

3.3.3. Zig-zag motion

Live fish may differ in the paths they take towards a goal. These differences may, for example, play a role in recruiting others in leadership scenarios. To enable investigations of the relative importance of these differences the RoboFish can be programmed to describe arbitrary paths to reach a goal (see section 2.2, motion type layer). Besides direct, linear motion, we implemented a motion type called 'zig-zag'. The current global target point is translated to a sequence of low-level targets that form a zig-zag pattern. These low-level targets are identified by the turning points of a sine wave along the main movement axis. The model parameters *zig-zag-period* and *zig-zag-amplitude* define the length of the path along the main axis for one sine period and the (orthogonal) distance of the turning points to the main axis. As a result, the robot

moves from one global target point to another on a zig-zag trajectory (see example track in figure 6).

3.4. Closed-loop dynamic cues: social interactions

Live fish might expect conspecifics to behave in a species-specific way. This might include appropriate behavioral responses to social cues (i.e., the behavior of other conspecifics). Any deviation of the observed behavior from this expectation might then decrease acceptance of the respective individual.

Our RoboFish system is able to respond in real-time to the actions of live animals (see section 2.2). The atomic behaviors (table 2) can be combined to form complex closed-loop behaviors. It is possible to define conditions under which logical branches (i.e., different subsets of atomic behaviors) are executed or terminated. These include virtually all information available in the programming language and data structures provided (timers, proximity or angular similarity, etc). In the following we describe the current set of closed-loop behaviors.

3.4.1. Approach shoal centroid/nearest neighbor/individual X

Given the list of atomic behaviors, the simplest possible closed-loop behavior is to constantly approach the shoal's centroid or a certain individual (e.g., the nearest neighbor). Due to the sigmoid forward velocity controller, the robot stops when its distance to the global target falls below a predefined threshold (defined by the sigmoid controller parameters). Collision avoidance is implemented rudimentarily. If live fish are detected within a virtual sensor area, the robot slows down by 50%. This sensor area is a rectangle of 3 cm width and 5 cm length, aligned with the current motion vector in front of the RoboFish. Note that no path correction is implemented.



Figure 6. Depiction of the ‘zig-zag’ trajectory. The RoboFish left the start cylinder (upper left) and moved along a zig-zag path to the diagonal corner. After reaching this corner, the RoboFish turned left and moved to the upper right corner. Here, it performed a circular path after arrival. This trajectory was used for Experiment I (see section 4.1).

3.4.2. Three-zones-model

We have implemented a model of shoal integration inspired by Couzin *et al* (2002). It describes fish shoaling behavior as a simple sequence of attraction, alignment and repulsion. Therefore, three concentric zones are defined around the robot. If the RoboFish detects its nearest neighbor within the repulsion zone (for the guppy: repulsion zone: 2 cm radius; alignment zone: 6 cm radius; Herbert-Read *et al* unpublished data), the atomic behavior *escape* is executed (table 2). If the nearest neighbor is detected in the alignment zone, the atomic behavior *align* is executed to match the orientation of that animal. If no fish can be detected in these two zones, the atomic behavior *approach nearest neighbor* is executed. The repulsion rule has priority over the other rules; if there are any fish present in the repulsion zone, only the repulsion maneuver will be executed. If there are no individuals within the repulsion zone and more than one fish in the alignment zone, the robot will execute the atomic behavior *align with shoal*.

3.4.3. Predator behavior

The predator behavior is a variant of the atomic behavior *approach shoal centroid*, with motion speeds larger than $20 \text{ cm}^{-\text{s}}$ and no collision avoidance.

3.4.4. Recruitment behavior

The recruitment behavior is composed of four atomic behaviors for approaching and integrating into the shoal, and to recruit animals to a predefined location in the tank. When far away from the shoal (>5 body lengths = 15 cm) the atomic behavior *approach shoal*

centroid is executed. The shoal might split in the course of executing the atomic behavior. The largest shoal is chosen for the continuation of the atomic behavior. When the robot has reached the shoal (distance to the centroid is less than 15 cm), the robot continues the execution for 20 more seconds. If afterwards it is still inside the shoal, it switches to the atomic behavior *approach tank location*. In Landgraf *et al* (2014) we chose the center of the tank as the target for the recruitment move. Refer to table 2 for further options of target points. On the way to the target point, we evaluate if the nearest neighbor stays close (<30 cm). If not, the robot executes the behavior *wait* for 5 s maximum. If after that time no fish has moved closer, the robot starts all over again with the atomic behavior *approach shoal centroid*. If at least one fish is detected within that 5 s time frame, the recruitment move is continued to the target point. If the robot reaches the target point, it executes an unconditional *wait* for 5 s, after which it starts again by approaching the shoal.

4. Experiments testing RoboFish acceptance by live Trinidadian guppies

In this section, we present data from a set of experiments that evaluate our recent improvements on all three proposed acceptance levels.

4.1. Experiment I: visual appearance level

We evaluated how guppies responded to replicas with and without glass eyes attached. To do so, we tested the response of six female guppies towards two identical

3D-printed replicas, the first one with and the second one without glass eyes attached.

4.1.1. Experimental setup

To initiate a trial, test fish were transferred individually into the RoboFish tank and placed in a removable Plexiglas cylinder in a randomly chosen corner (figure 6). The RoboFish was also located within the cylinder and, after a habituation period of 2 min, the cylinder was lifted using an automated pulley system. When the live fish left the cylinder, the RoboFish started moving with the natural stop-and-go motion pattern along a zig-zag path to the opposite corner (see figure 6; see descriptions above). When reaching this corner, the RoboFish moved to either the left or the right corner (chosen at random) where, finally, it performed a circular path (three circles) upon arrival (figure 6). Each trial was videotaped for subsequent tracking and we calculated the fraction of time each test fish spent within a radius of 20 cm (ca 6–7 times the body length of the replica). We chose this distance arbitrarily to have a fixed cut-off point. We used both natural swimming as well as zig-zag movement in this test to provide the test fish with the most naturally behaving RoboFish. Then, it is reasonable to compare live-robot interactions with live–live fish interactions to evaluate the effect of attached glass eyes. For this comparison, 24 pairs of live fish were tracked for 3 min in the same arena after they both left the aforementioned cylinder.

4.1.2. Results

The time live test fish spent together with another live animal did not differ from the time live fish spent following the replica with glass eyes attached, while they spent significantly less time following a replica without glass eyes (figure 7, one-way ANOVA with Fisher's least significant difference (LSD) *post hoc* comparisons: $F_{2,33} = 11.82$; $P = 0.0001$).

4.2. Experiment II: natural motion patterns

As shown beforehand, a replica with attached glass eyes that moved naturally on a zig-zag path led to interactions similar to that of two live fish. To further evaluate the role of natural swimming behavior for replica acceptance, we compared the acceptance of a naturally moving replica towards one that moved without natural swimming behavior.

4.2.1. Experimental setup

As an analogue to the experiment described in section 4.1, the RoboFish was moved in a path from the top left corner of the tank to the bottom right, followed by a turn and approach to the top right corner. No zig-zag movement was used here and the replica carried glass eyes. Six female guppies were tested with a RoboFish swimming with natural movement while a further six were tested without. In the

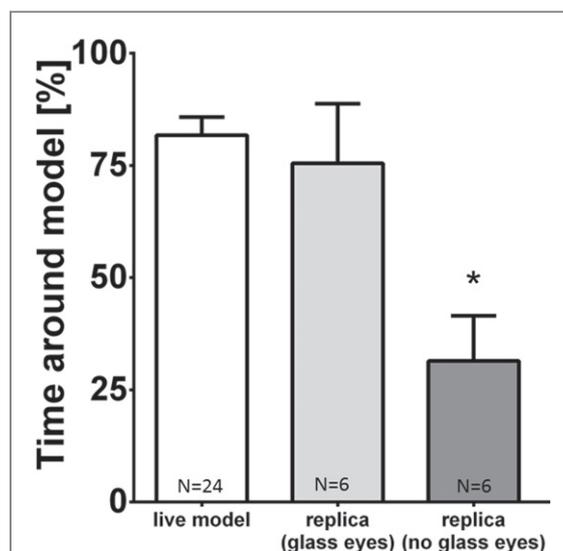


Figure 7. Acceptance of RoboFish with and without attached glass eyes by live guppy females. Depicted is the proportion of time the test fish spent within a radius of 20 cm around the replicas (mean \pm SEM) that were moved on a zig-zag trajectory (see figure 6). We compared the time spent around the replicas to trials where two live fish were allowed to interact (control) through one-way ANOVA followed by Fisher's LSD tests for pair-wise *post hoc* comparison. Asterisk indicates significant differences compared to other treatments.

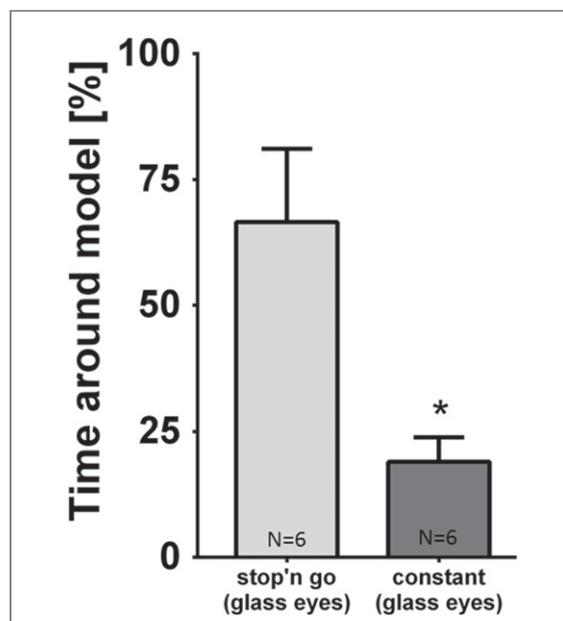


Figure 8. Acceptance of RoboFish moving with natural stop-and-go pattern or constant speed. Depicted is the proportion of time test fish spent within a radius of 20 cm around replicas (mean \pm SEM) that were moved either in the natural stop-and-go pattern or at a constant speed. We compared the time spent around the replicas via t-tests. Asterisk indicates significant differences.

latter case, the RoboFish moved with a constant speed of $6 \text{ cm}^{-\text{s}}$, which was also the maximum speed used in the natural swimming behavior. Subsequently, the videos were tracked with our tracking program and

the proportion of time test fish spent within a 20 cm radius around the RoboFish was scored.

4.2.2. Results

We found that fish tested with RoboFish exhibiting natural movements spent significantly more time near the RoboFish than those tested with RoboFish moved with constant speed (figure 8, Student's t-test: $t_{10} = 3.10$; $P = 0.013$). Thus, besides glass eyes (see section 4.1) also natural movement is important for the acceptance of the RoboFish by live fish.

4.3. Experiment III: close-range inter-individual distance (social interactions)

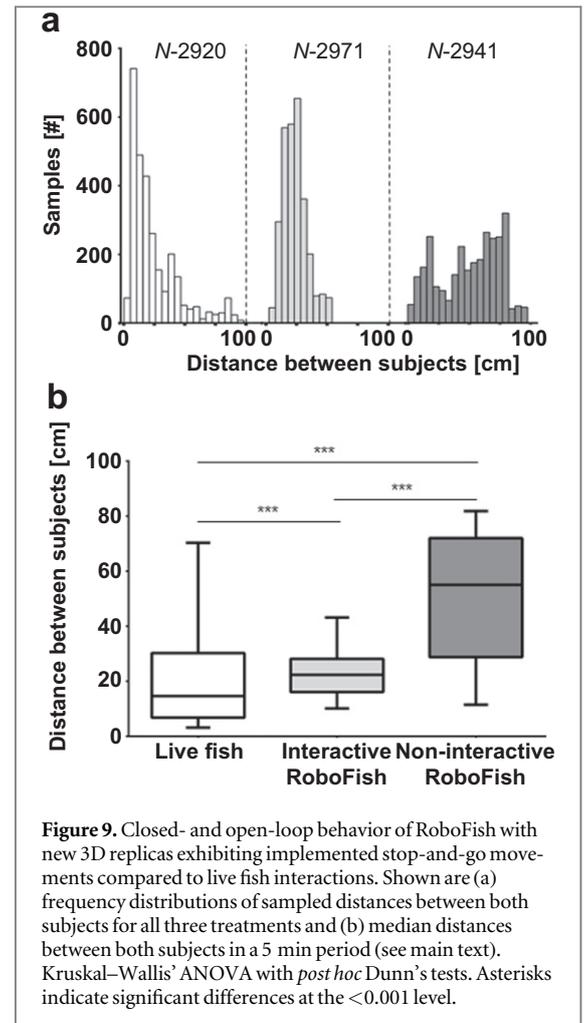
Previous work showed that an interactively moving RoboFish integrates itself into shoals of live guppies and then leads small groups of live guppies to the center of the tank, a region that is usually avoided (Landgraf *et al* 2014). However, it was not reported whether simple interaction rules used by the RoboFish to integrate itself into the shoal ('follow shoal center') lead to similar spatial interaction patterns as observed in shoals of only live fish. We tested whether the distance between a live fish and the interactively moving RoboFish ('approach shoal centroid, see section 3.3) or a RoboFish that only moved on a predefined trajectory (open-loop behavior, see section 3.2) were comparable to distances measured in pairs of live guppies without a RoboFish present. As a reminder, the RoboFish swimming in this closed-loop behavior will try to approach the center of a shoal of live animals, or in the case of only one live animal present, the actual position of that animal (see above).

4.3.1. Experimental setup

To initiate a trial, a single female guppy was introduced into the RoboFish arena and left undisturbed for 15 min to habituate to the test environment. We then placed the replica (with glass eyes) inside the tank and started video recording for 5 min. The replica moved in a square trajectory using the natural stop-and-go motion pattern keeping 10 cm distance to the tank walls. After this phase, the replica stopped for 1 min and began moving with the interactive *approach shoal centroid* behavior for another 5 min. Afterwards, we removed the replica and introduced a second live fish and videotaped them for another 5 min. Tracking of the fish was done using our fish tracking software with a sample rate of 10 samples/second (smoothing with 5 samples half window). We extracted the distance between both subjects for each sample and compared average distances among all three treatments using Kruskal–Wallis ANOVA (followed by *post hoc* Dunn's tests).

4.3.2. Results

Distance distributions show a high similarity between the treatment with a live model fish and a closed-loop



moving RoboFish (figure 9(a)). Nevertheless, the interactively moved RoboFish produced lower variation in distance than found in the live fish pair. This is obviously driven by the fact that RoboFish in the 'follow shoal center' behavior did not exhibit any own leadership tendency. Median distances between both subjects were similar when comparing pairs of live fish to a replica showing interactive behavior but notably higher when the replica was showing only an open-loop square movement (figure 9(b)). However, due to the high number of analyzed samples (ca 3000) per treatment (see figure 9(b)), differences in median distance between subjects in all treatments differed significantly (KW-ANOVA: $P < 0.001$; Dunn's test in all cases with $P < 0.0001$).

5. Conclusions and outlook

In the current study, we report on factors that might increase the acceptance of a biomimetic robot by live fish, the Trinidadian guppy (*Poecilia reticulata*). We proposed three levels of cues that influence the acceptance of a robot by live animals: (1) constant cues, (2) open-loop dynamic cues, and (3) closed-loop dynamic cues. On the level of constant cues, our study

shows that the attachment of glass eyes (substituting flat painted eyes) increased acceptance significantly. We then showed that on the level of open-loop dynamic cues, natural motion patterns exhibited by the RoboFish significantly increased the acceptance by live fish, while highest acceptance was reached when the robot further showed a zig-zag movement. Lastly, on the level of closed-loop dynamic cues, we provide evidence for the importance of interactive behavior of the robot to produce realistic interaction patterns with a live fish.

For the study of animal behavior using biomimetic robotic agents, the acceptance of a robot by live animals is crucial. While some species do accept any kind of object as a conspecific during a so-called imprinting phase (see works of Konrad Lorenz on birds, Lorenz 1935), often a minimal set of cues has to be provided to elicit acceptance (Krause *et al* 2011). Many teleost fishes rely heavily on visual cues (i.e., Price *et al* 2009) and we thus tried to first create replicas that closely resemble a live guppy as recommended for any kind of dummy used in behavioral research on fish. The attachment of realistic eye models to our replicas was then found to represent a prerequisite for proper acceptance in guppies. This is congruent with earlier studies on other teleost fishes. For example, Midas cichlids (*Cichlasoma citrinellum*) were found to interact less with eyeless replicas or replicas with eyes on unnatural body locations compared to replicas with natural eye dummies (Barlow and Siri 1994).

It is known that natural movement patterns are a key feature for the acceptance of dummies by live fish (Butail *et al* 2015). Krause *et al* (2011) thus recommended behavioral tracking and inclusion of fine-scaled movement patterns into the movement repertoire of biomimetic robots. We analyzed motion patterns of Trinidadian guppies and implemented several derived parameters into our robot's motion repertoire ('natural movement'). These improvements then resulted in an increased acceptance level of our replicas by live fish. As the presented parameters that describe the natural movement of Trinidadian guppies can be adjusted easily, our system is readily adaptable to other similar-sized species (including the use of appropriate replicas). Another interesting point to look at is the body motion during swimming, e.g., tail-beating. Several studies investigated the response of live fish towards replicas exhibiting natural tail-beating (see Butail *et al* 2015 for a review). Thus, constructing replicas able to perform species-specific tail-beats should obviously further increase replica acceptance. Furthermore, animals from the same species or population often differ consistently in their activity patterns, a phenomenon called 'animal personality' or 'animal temperament' (see Réale *et al* 2007, Conrad *et al* 2011). With the ability to adjust different moving parameters, our robot system can be used to simulate different 'animal personalities'. This further enables the fine-scaled investigation of how live animals react

upon (differently behaving) conspecifics, represented by controllable robots, that differ in many or just certain motion parameters.

As shown in an earlier work, even a robotic agent without glass eyes and natural movement was able to recruit live fish when moved interactively (Landgraf *et al* 2014): the robot alternated between strict shoal following and recruitment attempts to attract the shoal to a static location, the center of the tank. In the current study, we show that interaction properties (here: distance between agents) similar to live-live fish pairs can be reached when the robot is run in the closed-loop behavior *approach shoal centroid*. As the robot was not programmed to lead or recruit in this test, there is still a difference compared to live-live fish pairs detectable. However, the live guppy tested with the interactive robot neither escaped in a startle response nor froze, which are both well-known behaviors that fish display when encountering predators or otherwise dangerous situations (see Domenici *et al* 2011).

In our current closed-loop system, the experimenter is required to choose a set of parameters (zone ranges, approach speeds, etc). Those remain constant over the course of the experiment and throughout trials. However, recent research shows that individuals within fish shoals might themselves differ in those properties (e.g., Herbert-Read *et al* 2013, Romenskyy *et al* 2015). Likewise, the response of the shoal to individual actions might as well depend on the group's composition. We therefore hypothesize that, for a given task (such as shoal integration or recruitment to a location in the tank) the optimal parameter set depends on the individual differences of the shoal members. Currently, we are testing statistical tools to quantify the performance of the RoboFish system. Besides classical measures (e.g., the deviation of an observed distribution to a target distribution), we propose using the transfer entropy (Schreiber 2000), an information theoretic quantity capable of representing the information flow between dynamical systems. Recently, it has been used to quantify information transfer between live and artificial fish (Butail *et al* 2014, Ladu *et al* 2015a, 2015b). With a set of performance measures at hand, the robot might explore the parameter space in learning experiments and optimize its performance in a shoal integration or recruitment task. On the other hand, the transfer entropy might reveal aversive behaviors elicited by the robot and thus might be used in a negative feedback mechanism as well.

The RoboFish system can operate multiple robots in open-loop control using predefined motion paths. The current obstacle avoidance mechanism, however, doesn't support the simultaneous execution of closed-loop behaviors. We are currently adding a more sophisticated obstacle avoidance mechanism to enable more complex experimental designs in the future.

Our results indicate that certain properties of the robot-controlled replicas influence the overall acceptance, attraction and response patterns of live fish. In a scenario with realistic appearance, motions and interactive behavior, our RoboFish attracts guppies, which stay at natural distances from the robot. With the reported improvements of the RoboFish system, experimenters can replace live individuals in a group by biomimetic robots. Thus, a systematic manipulation and fine-scaled analysis of animal groups on the move is now possible.

Acknowledgments

The authors like to thank three anonymous reviewers for their valuable comments that helped to improve the manuscript substantially. We also thank R Akkad and J Schröer for their contributions to the RoboFish software. This research was partly funded through the Leibniz Competition (B-Types project; SAW-2013-IGB-2). Experiments involving robot – live fish interactions were performed in Trinidad, while live-live fish interactions were recorded at IGB and comply with current German law (approved by LaGeSo Berlin (Reg 0124/14)).

References

- Abaid N, Bartolini T, Macri S and Porfiri M 2012 Zebrafish responds differentially to a robotic fish of varying aspect ratio, tail beat frequency, noise, and color *Behav. Brain Res.* **233** 545–53
- Abaid N, Marras S, Fitzgibbons C and Porfiri M 2013 Modulation of risk-taking behaviour in golden shiners (notemigonus crysoleucas) using robotic fish *Behav. Process.* **100** 9–12
- Price A C, Weadick C J, Shim J and Rodd F H 2009 Pigments, patterns, and fish behavior *Zebrafish* **5** 297–307
- Barlow G W and Siri P 1994 Polychromatic midas cichlids respond to dummy opponents: color, contrast and context *Behaviour* **130** 77–112
- Bonnet F, Rétonnaz P, Halloy J, Gribovskiy A and Mondada F 2012 *Development of a mobile robot to study the collective behavior of zebrafish 4th IEEE RAS & EMBS Int. Conf. on Biomedical Robotics and Biomechatronics (BioRob) (Piscataway, NJ) (IEEE)* pp 437–42
- Brown C, Laland K and Krause J 2011 *Fish Cognition and Behavior* 2nd edn (Chichester: Wiley)
- Bshary R, Gingsins S and Vail A L 2014 Social cognition in fishes *Trends Cogn. Sci.* **18** 465–71
- Butail S, Bartolini T and Porfiri M 2013 Collective response of zebrafish shoals to a free-swimming robotic fish *PLoS One* **8** e76123
- Butail S, Polverino G, Phamduy P, Del Sette F and Porfiri M 2014 Influence of robotic shoal size, configuration, and activity on zebrafish behavior in a free-swimming environment *Behav. Brain Res.* **275** 269–80
- Butail S, Ladu F, Spinello D and Porfiri M 2014 Information flow in animal–robot interactions *Entropy* **16** 1315–30
- Butail S, Abaid N, Macri S and Porfiri M 2015 Fish–robot interactions: robot fish in animal behavioral studies *Robot Fish* (Berlin: Springer) pp 359–77
- Candolin U 2003 The use of multiple cues in mate choice *Biol. Rev.* **78** 575–95
- Cianca V, Bartolini T, Porfiri M and Macri S 2013 A robotics-based behavioral paradigm to measure anxiety-related responses in zebrafish *PLoS One* **8** e69661
- Conrad J L, Weinersmith K L, Brodin T, Saltz J B and Sih A 2011 Behavioural syndromes in fishes: a review with implications for ecology and fisheries management *J. Fish Biol.* **78** 395–435
- Couzin I D, Krause J, Franks N R and Levin S A 2005 Effective leadership and decision-making in animal groups on the move *Nature* **433** 513–6
- Couzin I D, Krause J, James R, Ruxton G D and Franks N R 2002 Collective memory and spatial sorting in animal groups *J. Theor. Biol.* **218** 1–11 (2002)
- Domenici P, Blagburn J M and Bacon J P 2011 Animal escapology: I. Theoretical issues and emerging trends in escape trajectories *J. Exp. Biol.* **214** 2463–73
- Faria J J, Dyer J R G, Clément R O, Couzin I D, Holt N, Ward A J W, Waters D and Krause J 2010 A novel method for investigating the collective behaviour of fish: introducing ‘Robofish’ *Behav. Ecol. Sociobiol.* **64** 1211–8
- Halloy J et al 2007 Social integration of robots into groups of cockroaches to control self-organized choices *Science* **318** 1155–8
- Herbert-Read J E, Krause S, Morrell L J, Schaerf T M, Krause J and Ward A J W 2013 The role of individuality in collective group movement *Proc. R. Soc. B* **280** 20122564
- Katz Y, Tunström K, Ioannou C C, Huepe C and Couzin I D 2011 Inferring the structure and dynamics of interactions in schooling fish *Proc. National Academy of Sciences* **108** 18720–5
- Krause J, Winfield A F T and Deneubourg J-L 2011 Interactive robots in experimental biology *Trends Ecol. Evol.* **26** 369–75
- Ladu F, Bartolini T, Panitz S G, Chiarotti F, Butail S, Macri S and Porfiri M 2015a Live predators, robots, and computer-animated images elicit differential avoidance responses in zebrafish *Zebrafish* **12** 205–14
- Ladu F, Mwaffo V, Li J, Macri S and Porfiri M 2015b Acute caffeine administration affects zebrafish response to a robotic stimulus *Behav. Brain Res.* **289** 48–54
- Landgraf T, Nguyen H, Forgo S, Schneider J, Schröer J, Krüger C, Matzke H, Clément R, Krause J and Rojas R 2013 Interactive robotic fish for the analysis of swarm behavior *Advances in Swarm Intelligence* ed Y Tan, Y Shi and H Mo Berin (Berlin: Springer) pp 1–10
- Landgraf T, Nguyen H, Schröer J, Szengel A, Clément R G, Bierbach D and Krause J 2014 Blending in with the shoal: robotic fish swarms for investigating strategies of group formation in guppies *Biomimetic and Biohybrid Systems* ed A Duff et al (Switzerland: Springer) pp 178–89
- Lopez U, Gautrais J, Couzin I D and Theraulaz G 2012 From behavioural analyses to models of collective motion in fish schools *Interface Focus* **2** 693–707
- Lorenz K 1935 Der Kumpan in der Umwelt des vogels *J. Ornithologie* **83** 137–213
- MacQueen J 1967 Some methods for classification and analysis of multivariate observations *Proc. 5th Berkeley Symp. on Mathematical Statistics and Probability (June 1967)* 1 pp 281–97
- Magurran A E 2005 *Evolutionary Ecology: The Trinidadian Guppy* (Oxford: Oxford University Press)
- Mikheev V N and Andreev O A 1993 Two-phase exploration of a novel environment in the guppy *Poecilia reticulata* *J. Fish Biol.* **42** 375–83
- Phamduy P, Polverino G, Fuller R C and Porfiri M 2014 Fish and robot dancing together: bluefin killifish females respond differently to the courtship of a robot with varying color morphs *Bioinspiration Biomimetics* **9** 036021
- Polverino G, Abaid N, Kopman V, Macri S and Porfiri M 2012 Zebrafish response to robotic fish: preference experiments on isolated individuals and small shoals *Bioinspiration Biomimetics* **7** 036019
- Polverino G, Phamduy P and Porfiri M 2013 Fish and robots swimming together in a water tunnel: robot color

- and tail-beat frequency influence fish behavior *PloS One* **8** e77589
- Polverino G and Porfiri M 2013a Mosquitofish (*Gambusia affinis*) responds differentially to a robotic fish of varying swimming depth and aspect ratio *Behav. Brain Res.* **250** 133–8
- Polverino G and Porfiri M 2013b Zebrafish (*Danio rerio*) behavioural response to bioinspired robotic fish and mosquitofish (*Gambusia affinis*) *Bioinspiration Biomimetics* **8** 044001
- Réale D, Reader S M, Sol D, McDougall P T and Dingemanse N J 2007 Integrating animal temperament within ecology and evolution *Biol. Rev.* **82** 291–318
- Romensky M, Herbert-Read J E, Ward A J and Sumpter D J 2015 The statistical mechanics of schooling fish captures their interactions (arXiv:1508.07708)
- Schreiber T 2000 Measuring information transfer *Phys. Rev. Lett.* **85** 461–4
- Serra J 1983 *Image Analysis and Mathematical Morphology* (New York: Academic)
- Spinello C, Macrì S and Porfiri M 2013 Acute ethanol administration affects zebrafish preference for a biologically inspired robot *Alcohol* **47** 391–8
- Swain D T, Couzin I D and Leonard N E 2012 Real-time feedback-controlled robotic fish for behavioral experiments with fish schools *Proc. IEEE* **100** 150–63
- Tinbergen N 1948 Social releasers and the experimental method required for their study *Wilson Bull.* **60** 6–51
- Webb B 2000 What does robotics offer animal behaviour? *Animal Behav.* **60** 545–58
- Wu K, Otoo E and Suzuki K 2009 Optimizing two-pass connected-component labeling algorithms *Pattern Anal. Appl.* **12** 117–35
- Zivkovic Z and van der Heijden F 2004 Recursive unsupervised learning of finite mixture models *IEEE Trans. Patt. Anal. Mach. Intell.* **26** 651–6