From behavioural analyses to models of collective motion in fish schools

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Fish schooling is a phenomenon of long-lasting interest in ethology and ecology, widely spread across taxa and ecological contexts, and has attracted much interest from statistical physics and theoretical biology as a case of self-organized behaviour. One topic of intense interest is the search of specific behavioural mechanisms at stake at the individual level and from which the school properties emerges. This is fundamental for understanding how selective pressure acting at the individual level promotes adaptive properties of schools and in trying to disambiguate functional properties from non-adaptive epiphenomena. Decades of studies on collective motion by means of individual-based modelling have allowed a qualitative understanding of the self-organization processes leading to collective properties at school level, and provided an insight into the behavioural mechanisms that result in coordinated motion. Here, we emphasize a set of paradigmatic modelling assumptions whose validity remains unclear, both from a behavioural point of view and in terms of quantitative agreement between model outcome and empirical data. We advocate for a specific and biologically oriented re-examination of these assumptions through experimental-based behavioural analysis and modelling.

Keywords: fish schools; self-organization; collective behaviour; animal groups; coordination; individual-based model

1. INTRODUCTION

Collective motion is a widespread phenomenon in biological systems, from the captivating beauty of starlings performing aerial displays over their roost at dusk, to the march of cells during wound healing. Such phenomena span all ranges of size, scale and number of constituent group members, spread among almost all environments. The striking similarities in observed patterns, and the finding that under certain conditions very different microscopic mechanisms can lead to the same behaviour at the collective level, have paved the way for the theoretical modelling of collective motion and its high-level properties [1,2]. These studies have revealed the power of self-organization in creating new forms and facilitating functions as a result of individual interactions. Yet, despite this endeavour and a growing interest in collective behaviour, very little is known about the actual mechanisms at work in many biological systems, making previous research, which has largely been based on general a priori modelling hypotheses, often inconclusive regarding the mechanisms and the nature (epiphenomenal [3] or functional) of natural collective processes. Advocating for an experiment-based modelling of individual behaviour leading to collective motion, we will focus here on fish schooling. After reviewing the extensive literature addressing the question of the functions and behavioural mechanisms involved in the formation and maintenance of fish schools, we examine the different types of fish school models that have been introduced, and we discuss aspects of these works that give rise to their experimental flaws and success. We then discuss some key behavioural unknowns that one

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One contribution to a Theme Issue ‘Collective motion in biological systems: experimental approaches joint with particle and continuum models’.
is facing when trying to construct realistic models, advocating for specific data collection and experimental analysis aimed at their resolution.

2. MULTI-SCALE APPROACHES OF SCHOOLING BEHAVIOUR

We must first make clear what the term ‘schooling’ refers to. Following Radakov [4], we consider that social aggregations of fish are fundamentally polyfunctional and adaptive, highly integrated and conditioned by an ecological context and its necessities [5]. It follows that the repertoire of collective behaviours exhibited in vitro may not fully reflect the complexity and diversity of this dynamical behaviour in the full context of environmental contingencies. Owing to the constant transitions of global behaviour occurring in nature for a given population [5], we must clearly separate the broad social phenomenon from its most obvious manifestations (figure 1). In a modelling and/or experimental context, schooling typically refers to the coordinated swimming of fish, independently of the factors that trigger the synchronicity. This phenomenological definition is oriented by our aim of an accurate and experiment-based understanding of individual behavioural mechanisms involved in synchronized swimming.

Schooling is widely spread among fish living in oceans and freshwaters. It has been estimated that 50 per cent of fish species school as juveniles, and that approximately 25 per cent of species school throughout their life [6]. Understanding schooling also has important practical implications; a large component of commercially exploited species school, and improvements of fisheries stock assessment accuracy and fishing techniques rely on understanding schooling behaviour. As a matter of fact schooling is relevant to many research fields in biology, including ecology, ethology, ichthyology, evolutionary biology and neurosciences, but also in statistical physics and computational sciences. Since the observations of Parr [7], a large number of studies have been carried out to characterize schooling phenomena, addressing the question of which schooling patterns are exhibited in natural or experimental conditions, and why. Species that exhibit schooling tendencies are found and studied over a wide range of natural environments, for example pelagic fish of the Baltic Sea and Atlantic Ocean [4], coral-reef fish in the Californian Gulf [5] and many freshwater fish. Field observations have primarily been conducted by means of aerial observations [4, ch. 2]. These have been supplemented by increasingly accurate sonar techniques allowing to access the size, form and density of actual schools: for instance, the multi-beam sonar of Freón et al. [8] and the emergent ocean acoustic waveguide remote-sensing technique allows instantaneous sampling of fish density over huge areas, revealing large-scale collective behaviour, i.e. diurnal aggregation and migration of herrings during spawning season (see Makris et al. [9] and Jagannathan [10] for a review). A recent work by Handegard et al. [11] used a high-frequency sonar imaging technique with a 2 cm spatial resolution and 24 m² span to track the motion of both schooling prey and group-hunting predators in a natural marine environment, demonstrating the importance of collective behaviour to the strategies used by both predators and prey. In large clupeid schools, for example, acoustic imaging suggests groups to be highly heterogeneous with vacuoles and nuclei, and irregular frontiers [8,12]. The degree to which such density variations can be explained by individual behavioural rules as opposed to environmental factors such as the influence of the recording vessel, oxygen consumption within such large groups [13] and flow features of the
aquatic environment are not yet understood. The amoeboid shape, along with elongated form of the school and limited vertical extension, seems to be shared characteristics of pelagic fish, but the measured mean density greatly varies between species [14].

Quantitative experimental approaches of fish schooling have been conducted prior to such technological advancements. The seminal works of Breder [15], Shaw & Sachs [16] and Radakov [4] have emphasized the mechanisms of information transfer among individuals within schools, suggesting this is a general, and likely valuable, adaptation arising from social aggregation. Radakov [4] described the coordinated movement of fish in a school of *Atherinomorus* as ‘waves of agitation’ that could reflect against obstacles and attenuate and ‘streams of agitation’ where the directional information of one frightened fish is either amplified by social interactions to propagate to the whole school, or dies out. Another series of experiments on various fish species swimming in school in a flow channel (Pitcher and colleagues on cods, pollock, herrings and minnows [17–19], following the method of Cullen et al. [20]) unveiled the structural properties, in a statistical sense, of the school by means of video-recording and analysis of the extracted three-dimensional positions, opening the way to modelling studies. The fact that most of these authors focused on structural similarities across taxa and situations should not obscure the fact that the mechanisms at work in creating such structures are deeply linked to an adaptive specific behaviour and an ecological context.

When trying to get functional (‘ultimate’) explanations for schooling behaviour, schooling appears to be intrinsically adaptive and polyfunctional (see Krause & Ruxton [21], for a review). In some cases, it can improve foraging activity (mechanisms reviewed in Pitcher [22, ch. 12]) such as when information can be obtained from the foraging behaviour of others to improve an individual’s own exploitation of a patchy resource (when the fact that the mechanisms at work in creating such structures are deeply linked to an adaptive specific behaviour and an ecological context.

Thus, they may be used effectively to determine specific behaviours, and they will bring us closer to an understanding of the mechanisms of the evolutionary convergence among organisms that exhibit apparently similar collective motion.

Review. Collective motion in fish school U. Lopez et al.

from an increased chance of one or some group members to detect cryptic predators (the so-called many eyes effect [31]) and mechanisms allowing fast information transfer across the school (the so-called Trafalgar effect [25]). Counterbalancing these benefits, predators may also prefer attacking large groups of fish or detect them more easily, as evidenced in recent experimental work [32,33].

Schooling has also been thought to confer hydrodynamic benefits if individuals adopt positions such that they exploit the shedding of vortex sheets from those ahead [34]. An elongated diamond-shape pattern and a phase opposition of neighbours’ tail movements in a column are the school features theoretically found to optimize energy recovery from vortices produced by other group members, and fish trying to increase their efficiency would thus behave so as to adopt this configuration. This hypothesis can be tested by measuring the energy consumption when swimming. Tail beat frequency, which has been demonstrated to be positively correlated with oxygen consumption for solitary fish [35], is used as a proxy of the effort of the fish. Recent experiments on schools of roach [36] and seabass [35] found a significant reduction in tail beat frequency of the trailing fish compared with those of the front. However, because of the indirect nature of the measurement, there is still no conclusive proof of an energetic saving when swimming in school, and it is worth mentioning that many previous studies were confounded by the fact that fish in large groups tended to be less stressed, and thus may be expected to use less oxygen. Furthermore, if gaining a hydrodynamic advantage on large fast-cruising clupeids schools that need to migrate between their spawning and feeding sites is obvious, it may not stand for smaller river fish that also exhibit schooling, a view supported by experimental studies by Hanke & Lauder [37]. All these examples illustrate more broadly how difficult it is to establish a direct link between function and behaviour.

The proximate causes of fish schooling, i.e. the actual behavioural rules followed by individuals of a given species, are still poorly understood, although they could be crucial in understanding the evolution of collective motion and the associated functional benefits described earlier. A lack of quantitative data on fish schooling, and the fact that multiple sets of behavioural rules may yield practically identical global behaviour [38], raises a serious obstacle for the identification of such rules. With the growing interest in methodologies to infer interaction rules, and in experiment-based modelling, paths are being paved to allow deeper investigations of the rules that underlie schooling behaviour in a variety of contexts, such as in open, or more complex, environments [39–42]. While they cannot capture the full diversity of behaviours likely seen under natural conditions, laboratory experiments on schooling have the advantage of being highly controlled, allowing experimentalists to isolate key features of the social behaviour in schools [43]. Thus, they may be used effectively to determine specific behaviours, and they will bring us closer to an understanding of the mechanisms of the evolutionary convergence among organisms that exhibit apparently similar collective motion.
3. INSIGHTS FROM FISH SCHOOL MODELS

3.1. From individual to collective behaviour

As the description of schooling has progressed in terms of its functions and interplay with ecological constraints, and in terms of experimental characterization of emerging patterns, the interest in developing a framework to bridge the gap between individual and collective behaviour becomes clear. A major improvement of our understanding of collective motion in fish has thus been reached through the effort on modelling fish school behaviour using agent-based models, which has permitted researchers to set hypothetical individual rules and test through numerical simulations the resulting behaviour at the school level. The first successful attempts of such models [44–48], sometimes coming from unexpected fields such as computer animation [49, demonstrated that despite some methodological flaws (few fishes leading to a dominant border effect [43; poor exploration of initial conditions, as pointed out later [50]), simple individual behavioural rules often referred to as ‘traffic rules’, with appropriately tuned parameters, were able to reproduce the collective behaviour of a fish school with its main features (cohesion, polarity, shape and structure).

Schooling was thus classified among the growing collection of self-organized biological phenomena [1]. An intensification of the modelling and simulation effort over the last decades yield an important collection of models and studies, shedding some light on the complex interplay between the individual and school levels, and subsequent methodological and conceptual issues [51].

We will first present the most common ingredients implemented in individual-based models of collective motion and then categorize the existing models by the mean of their mathematical proximity. Through this categorization, the diversity of problems tackled by modelling studies is evoked.

3.2. A typology of individual based models for fish schooling

An agent-based model of collective motion starts with the mathematical definition at the individual level of the swimming abilities of the fish, at least implicitly, and the behavioural algorithms that define its interactions with the other individuals. Although they vary much in mathematical complexity and formalism, most are composed of three behavioural rules based on the main properties observed at the school level: collision avoidance, directional orientation (and thus synchronization of direction of travel) and finally cohesion. The repulsion rule facilitates collision avoidance and typically is given the highest priority, as inspired by observation on animal groups [41] as well as modelling [52]. The tendency to match behaviour of nearby neighbours, which is also termed allelomimetic behaviour [53], is typically expressed in an explicit rule of alignment for an individual trying to match the speed and direction of its neighbours. Recent experimental evidence has suggested that it might not be an explicit behavioural rule [41,42], but rather that coordinated motion might be achieved using social repulsion and attraction only (as supported by theoretical models [54–56]). Finally, an attraction rule mimics a tendency to group with conspecifics in order to produce aggregation, a prerequisite of school existence.

Moreover, these rules are often completed by a stochastic component to account for the individual intrinsic behavioural stochasticity (as Kuhlia mugil [40]). This noise corresponds to the intrinsic errors made when acquiring information on neighbours, changes in the motivational state of the fish or local (uncorrelated among individuals) sources of environmental noise. In the same spirit, swimming rules have to be supplemented by a stochastic component accounting for the variations in swimming abilities of the individuals as well as the fine scale or complex interactions with the water we will not take into account (wake turbulence [34], induced flows [57]) as long as the retroaction between medium and individual is estimated negligible [58].

3.3. Synchronous self-propelled particles models

We arbitrarily put together under this designation all modelling efforts oriented towards the understanding of fish schooling where the individuals’ speed is kept constant or drawn into a probability distribution [44,45] reproducing experimental data [59] and does not change as a consequence of interactions with neighbours. An individual fish therefore moves in straight line between successive time steps, with speed \( c_0 \) and bearing \( \mathbf{d}_i(t) \) (directional unit vector). At each time step, a preferred direction \( \mathbf{d}_i(t + 1) \) for the individual is computed according to the direction \( \mathbf{d}_i(t) \) and relative position \( \mathbf{r}_j(t) = \mathbf{r}_i(t) - \mathbf{r}_i(t) \) of the other fish in a defined neighbourhood \( N_i(t) \) with \( n(t) \) neighbours. This update can be expressed by the following general equations:

\[
\mathbf{d}_i(t + 1) = \frac{1}{n(t)} \sum_{j \in N_i(t)} w(|\mathbf{r}_{ij}(t)|) \mathbf{d}_j(t) \\
+ \frac{1}{n(t)} \sum_{j \in N_i(t)} f(|\mathbf{r}_{ij}(t)|) \frac{\mathbf{r}_{ij}(t)}{|\mathbf{r}_{ij}(t)|} + \eta_i(t).
\]

The preferred direction \( \mathbf{d}_i(t + 1) \) is then normalized to a unit vector. The new position of the particle is updated as follows:

\[
\mathbf{r}_i(t + 1) = \mathbf{r}_i(t) + c_0 dt \times \mathbf{d}_i(t + 1).
\]

The first right-hand term of the preferred direction equation corresponds to the alignment rule, with a fish tending to match the average (simple or weighted) direction of its neighbours. The second right-hand term ensures repulsion and attraction, and it takes respectively negative or positive values when the neighbours are too close or too far away. The last term \( \eta_i(t) \) is a stochastic component (for the origins and consequences of stochasticity in this context, see [60,61]). The coefficients \( w(r) \) and \( f(r) \) are used to define the relative range and weight of attraction and repulsion/alignment (A/R/A). Some models include behavioural zones of some extent where a specific rule is applied ([44,47,60,62], on boı¨ds [49]); some adopt functional forms for the attraction/repulsion coefficient [63,64]. Other biologically relevant ingredients are usually added such as a...
blind sensory zone [65], body size and form [66], or fish individual characteristics drawn from field-observed distribution [44,45], so that the behaviour of particles is closer to that of real fish.

It is important to notice that the definition of neighbourhood on which each term is calculated is a crucial point to consider because of its consequences on the behavioural output. Three main definitions can be found in the literature that lead to very different behaviours at large scale: first, the metric neighbourhood [64,67], where all individuals are taken into account within a surrounding area of a defined range. Second, the topological neighbourhood that remains invariant with respect to density changes, as first discussed by Ballerini et al. [68] in connection to data gathered on starling flocks. This topological neighbourhood has proved to lead to robust cohesion of the school under predation [68], and it may be achieved either by considering a fixed number of neighbours according to their proximity (K nearest neighbours) [68,69] or by using the first shell of a Voronoi tessellation [40,70]. This geometrical tessellation defines a zone of danger [71] for each member of the school, i.e. a zone where a hypothetical predator is closer to this member than any of its neighbours. The selfish herd hypothesis assumes that a predator would most likely attack the closest fish, thus making the interest of any fish to reduce the area of its zone of danger. The first shell of a Voronoi tessellation contains the neighbours of a focal fish with which their respective zones of danger overlap a surrounding area of a defined range. Second, the topological neighbourhood has proved to lead to robust cohesion of the school under predation [68], and it may be achieved either by considering a fixed number of neighbours according to their proximity (K nearest neighbours) [68,69] or by using the first shell of a Voronoi tessellation [40,70]. This geometrical tessellation defines a zone of danger [71] for each member of the school, i.e. a zone where a hypothetical predator is closer to this member than any of its neighbours. The selfish herd hypothesis assumes that a predator would most likely attack the closest fish, thus making the interest of any fish to reduce the area of its zone of danger. The first shell of a Voronoi tessellation contains the neighbours of a focal fish with which their respective zones of danger overlap a surrounding area of a defined range. Second, the topological neighbourhood has proved to lead to robust cohesion of the school under predation [68], and it may be achieved either by considering a fixed number of neighbours according to their proximity (K nearest neighbours) [68,69] or by using the first shell of a Voronoi tessellation [40,70]. This geometrical tessellation defines a zone of danger [71] for each member of the school, i.e. a zone where a hypothetical predator is closer to this member than any of its neighbours. The selfish herd hypothesis assumes that a predator would most likely attack the closest fish, thus making the interest of any fish to reduce the area of its zone of danger. The first shell of a Voronoi tessellation contains the neighbours of a focal fish with which their respective zones of danger overlap a surrounding area of a defined range.

To make a connection between individual behaviour and schooling patterns, numerous synthetic studies have been carried out, systematically varying individual parameters and measuring their influence on observables at the local level (nearest-neighbour distance, preferred positions of neighbours), group level (polarity, group momentum, shape, structure) and population levels (group-size distribution) [74]. The outcome of various hierarchies between the A/R/A rules has been studied on the motion of small groups of fish [63,75] and on the equilibrium structure (i.e. under no influence of randomness) at the collective level [76]. A crucial point is the presence of sharp transitions in collective behaviour that were observed for little parameter changes. For example, a slight change in the radius of orientation (if near the critical point) yielded drastic changes at the school level in terms of polarization and structure, such as transition between schooling, milling and swimming, as shown in Couzin et al. [62].

This algorithmic simplicity at the individual level, witnessed by a limited number of parameters, and yet, the presence of a diversity of patterns at collective levels (swarming, milling, synchronized swimming), provides the opportunity to conceptualize general emergent properties through mathematical modelling [77]. The complexity can be reduced to an explanatory and predictive ideal mechanism, under logical or mathematical form, referred as a self-organization principle [1,78], bringing some amount of generality into collections of case studies. Nevertheless, the goal of such models is not to capture the precise behaviour of an individual fish but rather to identify the minimal general components required for schooling.

3.4. Asynchronous self-propelled particles models

A typical feature of models of collective motion is a competition between a stochastic component and a tendency to order, although it is important to note that stochastic effects may also facilitate the instatement of collective motion [79]. However, there is a different way to implement stochasticity, which has been recently investigated by Bode et al. [80]. Instead of updating in synchronous way the position and velocity of all agents and add to the set of rules a random component, the agent updates are made through a deterministic set of rules in a random order. Interestingly, this asynchronous update yields a topological-like behaviour [81], very similar to what has been deduced from analyses on starling flocks [68].

Even though this behaviour is reminiscent of the schools of Paracheirodon innesi (C. Becco & N. Vandewalle 2009, Experimental study of collective behaviours in fish swarms, unpublished data), where the continuous motion of the school is composed of the sum of individual bouts and pauses with no apparent synchronicity (figure 2a), Bode et al. emphasize that there is no direct link between the updating frequency and the actual locomotors events. Yet, this new approach has an interesting ability to match experimental data [80]: a simple variation of update frequency can reproduce the speed distributions observed in groups of three spine sticklebacks under various level of agitation as they are frightened, hungry or steady.

3.5. Social forces models

Besides their success in linking functional properties at the school level to behavioural mechanisms at the individual scale and some experimental success [82,83], it is unlikely that the self-propelled particles framework, as we defined it, has the ability to lead to models accurately reproducing experimental data of species, notably in explaining the experimental speed distributions and consequently the mechanisms responsible for speed synchronization. In particular, a series of simulation studies have shown that the mean speed of an individual could be considered as an emergent property as well [51,69,74]. In self-propelled particles models, fixed speed implies a direct proportionality between polarization and mean speed of the school. Viscido et al. [74] performed experiments on groups of four and eight fish over periods of 10 min, exhibiting large deviations to this property.

The social forces framework considers a school as Newtonian particles submitted to ‘social forces’ (attraction and repulsion [63], orientation, random force...
accounting for intrinsic stochasticity and complexity of animal behaviour [61,84] and physical forces. The inclusion of explicit physical forces into individual rules of motion is one of the main motivations for these models. Indeed, the introduction of drag is found to have a drastic effect on collective behaviour [74]. While it widens the modelling horizon and allows some analytical work [61,84], this framework increases the number of potentially arbitrary factors that have to be implemented in the model.

Hopefully, it comes along with a number of tools developed for particle physics: methods such as Force-Matching [39] (also adaptable to self-propelled particles models) or Force Mapping, further discussed in §3.6, allowing to find best-fitted social forces relatively to a set of data. A recent experimental work [82] brought an evidence of frontal preference in the influential neighbours of an assembly of Surf Scoters swimming against the drift currents. A social force model with $A/R/A$ rules supplemented with weak frontal preference (an early modelling hypothesis [48]) has shown a good agreement between observed and predicted structure (radial distribution, angular preferred position). However, even if the model was able to reproduce the observation data quite well, it has been calibrated with the best set of free parameters that optimized the simulated patterns towards the observed collective properties (namely the authors made their model fit at the collective scale). In such a case, it is well known that several models can be fitted to a dataset at the collective scale, simply because the search for the best match is unconstrained and can be performed for each model, so that the collective level underdetermines the individual level.

### 3.6. Statistical physics of collective motion

An intense interdisciplinary work exists over individual-based modelling, particularly with statistical physics, following the seminal work of Vicsek [60]. The reader interested in the treatment of the problem by statistical physicists is referred to the reviews of Giardina [85] and Vicsek [86]. Tools initially developed for the study of out of equilibrium physical or chemical systems are adapted to the problem of living organisms. These methods aim at investigating possibly universal features of collective motion over diffusion, long-range order or presence of high-order and high-density regions at the onset of collective motion [87], named travelling bands. They may be analytical, through translations of agent-based models to Eulerian descriptions (in terms of continuous velocity and density fields), either phenomenologically [88] or analytically derived [89]. This approach aims at the understanding of the general mechanisms by which local rules lead to large-scale synchronization, those mechanisms being thought to be rather independent of the detailed nature of the systems’ components. This idea of independence of the large-scale behaviour relative to fine behavioural details is inspired by the existence and similarities of collective motion phenomenon in very different species and even in non-living systems. We think that for being crucial in the understanding of the ubiquity of collective motion phenomena in biological systems, this statistical physics approach does not aim to address the behavioural mechanisms that govern the dynamics of these phenomena. Collective motion in biological systems is rather seen in analogy with an out-of-equilibrium phase transition from a disordered phase where no global order is found to an ordered phase in which the system (i.e. the school) is highly polarized [60]. This critical change in global behaviour is obtained by varying the value of a behavioural parameter such as noise [60,90], blind angle size [65], speed [91], alignment tendency [62] or a ‘strategy parameter’ [92], which ponders a behavioural compromise between aligning with neighbours and reacting to their direction changes. The validity of this view finds some support in the experimental work of Becco et al. [93] that showed that such transition from disorder to order can be obtained by increasing

![Figure 2](http://rsfs.royalsocietypublishing.org/Downloaded from on June 23, 2017)
the density of Tilapia fish in a shallow water arena. Increasing density, in the Vicsek model, is equivalent to decreasing the noise, as the directional information transfer during fish ‘collisions’ is favoured by density. Interestingly, in an equivalent experimental set-up on another species, Gautrais et al. [40] found the inverse effect of density on global order, the school being unable to form beyond a certain density, underlining that at the intermediate level of size and number of an experimental set-up, the school can be dominated by fine behavioural details and yield a much different global behaviour than its large-scale statistically predicted one. Another rapid transition from disordered to highly synchronized behaviour at a critical density has been found in large population of spawning herrings by Makris et al. [9].

3.7. Self-organization and functional properties

Nevertheless, modelling is crucial to understand how does biological functions emerge from interactions between individual components. Among biological functions of long-lasting interest [4,94] is the transmission of information among the school, studied and heuristically defined with self-propelled particles and social force systems [86]. In these modelling frameworks, transmission of information can be defined, for example, in the terms of time needed for a particle to propagate its influence through a given fraction of the population [92], and thus its optimality (i.e. the maximization of its measured value) associated with a set of individual parameters. These works also allow some insights on how collective sensing [23] and decision-making [95] can be achieved in the schooling phenomenon. Striking is the demonstration of the possibility of a purely collective memory, the school being able to encode in its structure the memory of its previous state, a hysteresis being observed when slowly going from disorder to order and back acting on the behavioural parameters of the individuals [62].

Also successfully explained by a modelling approach is the mechanism of self-sorting of individuals in a school [62]. Costs and benefits of being part of a school vary as a function of the individual position within the school, a hungry individual being more likely to take a risk, but more successfully forage, on the edge [22]. In a large school or when its horizon is crowded, the fish cannot direct itself to its area of inter- 

4. OPEN ISSUES FOR THE INVESTIGATION OF COGNITIVE AND BEHAVIOURAL MECHANISMS INVOLVED IN SCHOOLING

With several models exhibiting similar global-collective patterns provided they are appropriately tuned (see the discussion on this particular issue in Gautrais et al. [40] and Weitz et al. [38]), conclusions on the specific mechanisms ensuring those different functions in various species are still out of reach. A way to reconcile data with models and ensure that one does not predetermine the behavioural rules to get a desired schooling behaviour is to proceed with a bottom-up approach on each species. This method is illustrated by a recent experimental work that leads to a model reproducing quantitatively the behaviour of fish both at individual and collective levels, based on a fish kinematic with interesting long-time diffusive properties [40,96]. The idea is to build a model incrementally from scratch, validating at each step the modelling choices through a specific experimental design. In the past, the very same methodological framework has been successfully applied to characterize and model individuals’ interactions that govern collective behaviour in pre-social and social insects [97–99].

In this approach, we believe that there exist some key behavioural components that have to be carefully evaluated. A first important component is the kinematic that characterizes the motion of a single fish. Depending on its intrinsic features, it may or may not facilitate the inference of social interactions at stake in the school. Then, the type of information (i.e. the stimuli) gathered by an individual to control its movement is also crucial, especially when the perception or the behavioural reactions of a fish change in different environmental conditions. Assuming that these stimuli can be somewhat decomposed into a sum of pair interactions, one has then to consider which neighbours a fish is going to interact with. If this assumption is wrong, one has to identify the kind of information processing a fish is doing, namely how the stimuli are combined and what are the resulting consequences on the motion of the fish. Finally, a last issue concerns the impact of endogenous physiological and behavioural changes on data collection and analysis.

4.1. Characterizing the spontaneous motion of fish

Schooling phenomena occur in species that have evolved widely different swimming abilities and behaviours. Constrained by biomechanics, the elected swimming mode (see Sfakiotakis et al. [57] for a review) can lead to a continuous motion, as for most pelagic fish (see fig. 2b,c from K. mugil [100] or cod, saith and herring [19]), or to discontinuous burst-slide swimming (fig. 2a, from C. Becc & N. Vandewalle 2009, Experimental study of collective behaviours in fish swarms, unpublished data): the fish propels itself intermittently and then slides until viscosity stops the motion. In the latter case, individual swimming speed is highly variable, in particular for small river fish such as zebrafish (Danio rerio) or firehead tetra (see
4.2. Inferring interactions between individuals

Recently, several studies have explored ways to infer social interactions directly from experimental data rather than trying to test a priori rules with the satisfying properties at the collective level. The force-map technique [41] and the non-parametric inference technique [42] have been used to estimate from experiments with two fish the effective turning and speeding forces experienced by an individual, once the relevant variables on which they may depend have been chosen. In the force-map approach, the implicit assumption considers that fish are particles on which some neighbours may be reconsidered with regard to absolute information such as the position and speed of other individuals. The spontaneous motion, i.e. the limit case of a non-interacting fish defined as a constant speed random walk with correlated successive orientations in Gautrais et al. [100] and as a Langevin process for the social force model with drag in Viscido et al. [74], generates different large-scale diffusive properties [96].

Furthermore, when trying to characterize from experimental data the interactions between individuals in a fish school, one must start with a ‘null-model’ that adequately characterizes the motion of an isolated individual (see Katz et al. [41] in which the analysis of fish interactions is performed under an implicit social force assumption).

4.3. Acquiring and updating information on neighbours

The main sensory channels involved in schooling are vision [101] and the lateral line used to detect movement and vibration in the surrounding water [102,103] (see von der Emde et al. [104] for physiological and ecological considerations). Both channels have different properties: they act respectively at long and short range, vision operates in both the near and far field, whereas the lateral lines are limited to the near fields; and they also depend on the physical context (light, opacity, water flows). And both seem equally crucial [105], as a lateral line-disabled fish will not be able to school [103] and a blind fish will not be able to join its school if he loses its wake [102].

More important than the physiological processes involved in the acquisition of information is the kind of information a fish acquires and how it maps these estimates to motor control programmes. The assumption that a fish acts on the basis of discrete and absolute information such as the position and speed of some neighbours may be reconsidered with regard to the possible states of the system. The spontaneous motion, i.e. the limit case of a non-interacting fish defined as a constant speed random walk with correlated successive orientations in Gautrais et al. [100] and as a Langevin process for the social force model with drag in Viscido et al. [74], generates different large-scale diffusive properties [96].

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recent works. We can think of a more continuous and
global kind of information such as that driving the
motion of pedestrian crowds [106]. This is found to
direct a pedestrian towards the locally less crowded
area estimated with the angular density measure,
which is by itself a continuous and local variable.
Lemasson et al. [73] have introduced an A/R/A model
with neurobiological mechanisms of processing and
integrating the information. This model goes well
beyond the usual modelling hypothesis that mainly con-
sists of a direct calculation using the absolute positions
and velocities of neighbours. The angular position,
speed and direction of neighbours' images on the
retina of focal fish are integrated to ponder and trigger
its behavioural reactions. The model implements selec-
tive information processing, using key properties of
image detection and motion forecasting to select the
set of neighbours eliciting each of the three behavioural
reactions: attraction, alignment and repulsion. How-
ever, we are far away from deriving behavioural
mechanisms from the present understanding of the
actual cognitive and sensorimotor processes at work in
each schooling species. Nonetheless, the insight gained
on what information is actually perceived by an individu-
also enables us to make more realistic hypotheses
even if the complexity is increased.

Together with the issue of which type of information
is used is the coupling between the motion of the
individual and the perceptual capabilities of fish. In
the Lemasson's model [73], the matching response is
defined proportional to the speed of individual fish,
the displacement of an object on the retina of the individu-
ally being proportional to the speed of this object.
From an ecological point of view, half the species of
fish move intermittently [107], and among the benefits
gained from this type of locomotion may stand an
increased sensitivity to the surrounding while resting.
Pauses on the move allow a stabilization of the visual
field and an increase in the signal-to-noise ratio from
the lateral lines [108]. It is worth mentioning that the
dynamic correlation between cruising individual
speed and school structure, already noted by Aoki [59],
has been experimentally captured by the bottom-up
modelling approach of Gautrais et al. [40] through a
dependency on swimming speed of the main coefficients
controlling interactions between fish, namely the weights
of positional and directional information, that may have
a physiological origin. As shown in figure 3, increasing
swimming speed leads to an increase in group polarization.

4.4. Determining which neighbours a fish is
interacting with

From the STARFLAG project [109,110] that mapped
the three-dimensional structure of free-flying starling
flocks emerged strong experimental evidence for

Figure 3. (a) Time series of the alignment between two fish (left) for each experiment and (b) corresponding model simulations
(right), ordered by increasing fish speed. Speed is expressed in fish body lengths per second. The speed and polarization
interrelation is captured through speed dependency of the model's coefficient (text and figure from [40]).
topological-like interactions [68]. Each bird seems to pay attention to approximately seven nearest neighbours [68], suggesting how cohesiveness can be maintained in groups that exhibit such density variability. The neighbourhoods defined \textit{a priori} in a modelling study can be justified by physical sensory arguments (e.g. range of vision through diffusive medium, rapid attenuation of pressure waves) or by neurobiological arguments as in the selective attention model [73]. But considering the tremendous effects of the chosen neighbourhood on the outputs of the simulations in terms of cohesiveness, structure and dynamics of a school, the ultimate test should be a confrontation with experiments, i.e. with the behaviour of actual species. In a bottom-up modelling approach, provided that the interactions among fish have been correctly described, it is theoretically possible to quantitatively discriminate various neighbourhood choices through simulation and data collection across various scales (figure 4). But so far these effects are hard to observe in experiments because of the geometrical constraints due to the finite-sized arena [40].

The quantitative observation of a free-swimming school being uneasily achieved, we might consider designing experimental and analytical techniques, allowing us to discriminate between competing hypotheses. The necessity of an adequate experimental design relative to an analysis tool is stressed by the recent development of Bayesian inference methods [111]. In these conditions, a Bayesian methodology is shown to have the ability to validate a model against experimental data that covers sufficiently different configurations, i.e. experimentally sampling a transitory rather than static evolution. Reproducible experiments have to be designed in order to study such transitory phases. One could think of provoking the dispersion of a school with a device simulating an attack, allowing us to record the transitory phase of grouping from an initial dispersed condition. A recent work by Herbert-Read \textit{et al.} [42] using a classical experimental set-up has shown that the social force most representative of the data was essentially acting on a single nearest neighbour, constituting evidence for a single nearest-neighbour interaction for this species. In their methodology, the inferred social force is fitted into an artificial neural network using the maximum-likelihood method, and thus not explicitly parametrized. As such, it does not provide a straightforward way to formulate a model.

\textbf{4.5. Determining which ways are used by the individual to integrate information}

An individual may take into account information from various neighbours to control its next move. It may be expressed in a modelling framework as a combination of pair interactions, e.g. by summing [69] or averaging [50]. The limited cognitive abilities at work nonetheless
make suspect some utterly complex calculations over a large number of influential individuals. Recent experimental work by Katz et al. [41] suggests that integration of information cannot be seen as additive social forces, and rather points towards synergic or averaging combination of respectively speeding and turning forces. While modelling the motion of another species, school motion was best fitted when averaging the influences, the overall intensity roughly equalling the intensity of random influences.

In pedestrians, it has been shown that simple heuristics applied by an individual to the whole sensorial environment may match both requirements of low cognitive complexity and high efficiency at the collective level [106]. In that case, individuals are found to direct their motion towards the less-crowded angular direction. This rule is equivalent to finding the minimum of a local density landscape; a pedestrian, through visual information processing, may easily find an approximate solution but the rule is intrinsically hard to describe as a combination of pair interaction. We may remain aware that the reaction behaviour can be based upon a global stimulus that cannot be decomposed further, thus making the leap from pair interactions to whole-school interactions reciprocally hard to achieve formally. A similar heuristic rule leading to a global herding has also been used in a model [72] illustrating how the selfish herd hypothesis [71] could work efficiently. In this so-called local crowded horizon mechanism, each individual evaluates the density of the herd along all directions and directs its motion towards the angular direction in which the crowd density is the highest. Doing so, each individual considers the presence of all neighbours pondered by a ‘visual function’ that decreases according to the distance. This approach could be refined by taking into account only the influence of visible neighbours, through integrating the shape characteristics of school members, thus making the definition of the local crowded horizon compatible with what the fish can actually perceive.

4.6. Determining group size effects and their influence on the reactional state of fish

Adaptive properties at the collective level emerge from the behaviours of the interacting individuals that react to biological cues such as predators, food resources or to physical cues (such as light intensity, temperature) that can be controlled in a laboratory experiment. These stimuli may elicit punctually a stereotyped response (such as C-start elicited by water flows similar to a predator suction) but may also affect the internal state of the individual, leading to mid-term changes in behaviour. Several studies tried to capture this behavioural switch, with some success either with data analysis only [112] or in a self-propelled particles framework. Tien et al. [113] evidenced a neutral zone and a fall in nearest-neighbour distance when frightening schools of fish swimming in a pond. Another study by Hoare et al. [83] exhibited the link between group size selection and internal state eliciting an anti-predator response, hunger, and compared it with a control steady state.

In these examples, the effect on behaviour of a change in the internal state of fish is captured through the modification of the behavioural parameters of the model. As a matter of fact, the accurate modelling of fish behaviour allows measuring behavioural switches as variations of the behavioural parameter of the model. This has been shown for instance by Gautrais et al. [40], who detected a change in behavioural parameters with increasing density, leading to a disordered swimming once a critical density has been reached. It is worth noting that in that particular case, the individuals may change their behaviour relative to the density [91]. This additional coupling, namely the influence of the school as a whole on the behaviour of its constituent individuals, is a topic that we may carefully consider in future investigations.

To limit the impact of the behavioural variations due to non-physical factors such as habituation or any variation in the internal state of fish, it is prudent to get an estimation of the behavioural variability in the long term. A series of experiments led by Miller & Gerlai [114] on zebrafish explored quantitatively the effect of habituation on fish behaviour with the experimental arenas (no effect) as well as the effect of food presence (lowered density) and exposure to aerial model predator (no habituation, punctual effect).

5. CONCLUSIONS

In trying to understand why fish school evolutionarily, biologists have identified several emergent functional ‘supra-organismic’ properties that may benefit the individuals that belong to a school. But an accurate knowledge of behavioural mechanisms and interactions involved in schooling is also important to understand how these properties emerge. Decades of modelling and an increasing data collection aimed to understand the connection between individual interactions and school properties. Numerous modelling frameworks have been developed, and shed light on the potential mechanisms driving school formation, maintenance and patterns of motion. Most of these models represent idealized a priori behavioural algorithms that make their theoretical study easier. In searching for the actual behavioural mechanisms at work in fish, one could make a simple comparison of large-scale data with simulation output. However, it is hard to find biologically relevant individual mechanisms with such a top-down approach because of the strong coupling between individual behaviour and external cues, be they ecological or physical, the internal state of fish and finally the output of the school itself.

We have emphasized a set of major and unknown behavioural components that are likely to play a crucial role in schooling. As all these elements are coupled with each other, we suggest long-term incremental modelling work in direct confrontation with experimental data that may result into their characterization. The first component is the motion of a single fish, poorly considered up to now because of its lack of generality. It has to be carefully characterized and modelled so as to uncouple its consequences on school behaviour from those that result from interactions among fish. These interactions are a second important component already
investigated through new methods of data analysis that prove their ability in questioning the validity of a priori model assumptions for specific fish behaviour. Third, the nature of the stimuli used by an individual to control its trajectory is also crucial, as their perception may also depend on the fish motion and the environmental conditions. Fourth, the neighbours considered by a fish and from which stimuli are integrated into a behavioural response. Several hypotheses, namely metric, topologic or dynamic neighbourhood, have emerged from simulation studies that now require some experimental validation. Then, there is the question of the integration of the influence of a discrete number of neighbours. This is a rather complex cognitive hypothesis that is in competition with much simpler heuristics based on visual processing. Finally, a last issue concerns the impact of endogenous factors such as physiological and behavioural changes that may strongly impact data collection and analysis. The knowledge gained on such behavioural components is relative to a species. But we may hope that, after deciphering several behavioural mechanisms across different taxa, we will be able to identify several classes of fish school models.

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REFERENCES


6 Shaw, E. 1978 Schooling fishes: the school, a truly egalitarian form of organization in which all members of the group are alike in influence, offers substantial benefits to its participants. Am. Sci. 66, 166–175.


