Throughout the natural world, we observe large-scale phenomena that derive from the combined activity of smaller entities, termed “emergence”. Perhaps the most fascinating emergent properties are those observed through the collective behaviour of animal groups, such as flocks of birds or schools of fish. Through collective behaviour, emergent consequences of individuals' behaviour enhance the cognitive abilities of the group as a whole, termed collective intelligence. Studies of collective intelligence typically focus on the ecological advantages of collective behaviour and the behavioural mechanisms of their execution. The latter have been studied extensively (REF), and include both leader-follower and decentralized (aka “swarm”) intelligence models (Ioannou, 2016). Decentralized intelligence is the most purely emergent model of collective intelligence, wherein information is distributed evenly across the group and cognition occurs through the resolution of individual interactions. As a notable example, Berdahl *et al* (201X, REF) demonstrated collective perception in fish schools by exposing the group to patterned light/shade gradients. Individuals' responses to local light intensity affected an emergent optimization response.

We can generalize collective intelligence to a biological representation of decentralized information processing. Without a central control structure, decentralized processes are robust against fluctuations in information flow and disruptions in the processing network itself. For decades, decentralized processing has been a prominent strategy for applications of engineering and robotics (Durrant-Whyte \*\*\*\*and Henderson, 2008). More recently, decentralized processing has been proposed in neural network models of multi-modal sensory integration (Zhang *et al*. 2016). In this model, neurons form filter modules with reciprocal connections between modules that robustly integrate information in the brain. Zhang *et al* (2016) demonstrated that a decentralized model of neural information processing performs optimally in conditions of changing stimuli. The use of decentralization in robotic and neural models of information processing suggests that decentralization is a powerful strategy in systems that process very complex information.

What is the capacity of collective intelligence to process complex information? Can collective systems process more than the ecology-centric tasks that are typically demanded of animal groups? The goals of this study are to demonstrate the capacity of collective intelligence systems to process abstract information, and to compare and contrast collective and neural models of decentralized information processing. Exploring decentralized processing through a novel model system may provide a new angle from which to pursue the frontier of information science.

**Research questions:**

**Objective 1**: Demonstrate decision making in fish schools.

A complex task of information processing is to generate a binary decision from noisy information. Decision-making studies in primates aim to resolve how networks of neurons integrate noisy information to make a decision. For this task, experimenters present primates with visual stimuli of moving dots that move either left or right with variable coherence (“Variable coherence random dot motion, or VCRDM”, Shadlen & Newsome, 1996). The primate's task is to determine whether the majority of motion is leftward or rightward. By varying the parameters of VCRDM stimuli and recording from specific brain regions, it has been possible to characterize information processing with tremendous specificity (REFS).

Large schools of fish at swim in circular arrangements, called milling. Typically, milling is interspersed with translational movements, and milling direction changes frequently. These directional changes are a result of hundreds or thousands of individual conflicts among individuals, and therefore milling direction serves as a binary readout of a collective decision. Through recent pilot experiments, I have found that schools of fish (sunbleaks, sticklebacks, zebrafish) robustly follow moving dots projected onto the arena floor (outlined in methods; Bath & Couzin, unpublished data). With this method, it is possible to control milling direction by presenting clockwise or counter-clockwise rotating stimuli. By varying the coherence of rotation direction, it is possible to conduct experiments analogous to primate VCRDM, using large (1000 or more individuals) schools of fish.

With an experimental paradigm analogous to VCRDM in primates, it is possible to address questions of information processing in collective systems. Do larger groups perform better at discrimination tasks? To what extent do collective decisions resemble neural decisions, with respect to relationships among coherence, variability (etc) of VCRDM stimuli? To what extent do they differ? Assuming that some properties of decision-making processes are universal, collective decisions may provide a complementary paradigm to neurological studies, particularly with respect to connectivity. In neural decision-making networks, the precise connectivity of neurons is impossible to observe, and precise interaction of information is unknown. In collective systems, the analogous component to neural connectivity is the local interactions of individuals. These interactions can be observed, providing a framework to observe information processing of the entire system.

There are of course many differences between neural processing of decision-making and the collective counterpart. Neural processing requires constant connectivity and is arranged in a hierarchical way, with motion sensitive layers, summating layers, confidence layers, etc. On the other hand, collective processing exhibits dynamic connectivity and non-hierarchical structure. Nonetheless, comparing and contrasting different solutions to similar problems will be generally informative to the problem of emergent information processing.

**Objective 2**: Determine filter properties of individual fish responses

Emergence in physical systems is common, but requires either extremely large systems or extremely low noise in order for supervening processes to emerge. For example, consider two circumstances in which the rotation of the Earth is detectable by the Coriolis effect. On a large scale, cyclones in the northern and southern hemispheres rotate in accordance with the unbalanced force of the Earth's rotation on the turbulent atmosphere. On a smaller scale, one can observe the Coriolis effect in the vortex created by a draining pool of water, but only if the water is very still (Shapiro, 1962).

Biological systems, on the other hand, make particularly good use of emergence to solve problems. Even in small, dynamic contexts, emergent properties reliably enable group-level functions. How do biological agents enhance the efficacy of emergence? Animals perform cognitive functions that form an additional layer of processing. Interaction of individuals serves to compare local estimates at this layer. Thus, the additional layer of processing in biological systems is likely the source of enhanced emergent properties in collective intelligence.

But what aspects of individual signal processing contribute to enhanced emergence? Presumably, there is a set of environmental stimuli that cause robust behavioural responses. Through individual closed-loop experiments (outlined in Methods), it should be possible to determine the relationship between visual stimuli and behavioural response, thus characterizing the individual-level processing of the system.

Understanding individual-level processing will provide important information for mathematical and analytical models of collective behaviour, and enhance the efficacy of external control of fish behaviour (relevant to Objective 3). Perhaps more importantly, understanding the relationship between individual processing and emergent behaviours may provide key insights relevant to information technology by distributed processes. Additionally, comparing and contrasting individual-level processing across animal species may provide insights into how specific individual processing parameters contribute to emergent behaviours at the group level.

**Objective 3**: Use fish schools to characterize distributed conflict resolution

Through objectives 1 and 2, I expect to refine experimental techniques for controlling the locomotion of captive fish. Given this level of control, it should be possible to create group scenarios that are critical to test specific hypotheses, but that rarely occur in nature. This technique will promote a more hypothesis-driven approach to testing models of collective information processing, and will not be limited to naturally occurring group conformations.

Using this method, it should be possible to generate group configurations with highly conflicting information. By repeatedly observing the resolution of prescribed conflicts, it should be possible to generate models of information processing in the decentralized system of the fish school.

In summary, the goal of this study is to explore the processing power of animal groups by demonstrating binary decision-making and characterizing important properties of the processing units (fish) and components of the interaction between them.

**Methods**

**General approach**:

The main approach of this study utilizes visual stimuli presented to schools of fish. Fish will be placed in shallow aquatic arenas of either 1200mm or 3000mm width. Using a beamer mounted above, images will be projected onto the floor of the arena. Infrared lighting and imaging will allow the fish to be observed at high contrast, unobstructed by the visual stimulus. Groups ranging in size from 1 to 2000 individuals will be tested for response to stimuli specific to each objective. Two species of fish will be tested: the sunbleak (*Leucaspius delineatus*) and the three-spined stickleback (*Gasterosteus aculeatus*). These two species demonstrate strong schooling behaviour but exhibit moderate differences in the type and degree of schooling. Also, both species are abundant and several thousand individuals can be easily procured for this study.

The data analysis strategies for this study make use of automated fish tracking software (REFS) to describe positional relationships between individuals. This highly quantitative approach allows for detailed description of behaviour by a broad range of metrics, and is amenable to analytical modelling.

**Objective 1**: Demonstrate decision making in fish schools.

The purpose of this objective is to establish a decision-making paradigm in collective behaviour of fish, through analogous repetition of an experimental paradigm used in neural decision-making: VCRDM. In VCRDM, dots move semi-randomly with a proportion of the dots moving left, and the remainder moving right. The experimental subject's task is to decide the majority direction of motion. The difficulty of the task is determined by the coherence, or the proportion moving left or right, of the stimulus.

A modified version of VCRDM will be presented to groups of fish. In order to allow continuous response from the fish as they move, the left-right motion of the classic VCRDM stimulus will be modified to clockwise-counterclockwise rotation. Throughout the experiment, individual fish will respond to both local motion, which will vary in coherence and stimulus strength, and the motion of the neighbouring individuals. The behavioural responses will be recorded, as well as the visual stimuli, such that the social and visual responses of each animal can be resolved.

The experiment will be repeated at a broad range of group sizes and levels of coherence. I predict that larger groups will respond more accurately to lower levels of coherence.

**Objective 2:** Determine filter properties of individual fish responses

This objective aims to characterize the visual stimuli that strongly elicit behavioural responses from fish. By presenting orientation-adjusted stimuli to solitary fish, it will be possible to obtain an estimate of the innate behavioural responses to specific stimuli in the absence of social cues. For example, a black circle approaching from a 15 degree angle with a relative velocity of 100mm/s may evoke an avoidance turn. Or an expanding shape centred on the head of the animal may evoke and escape response.

The experimental strategy centres around closed-loop tracking of a single fish. Using computer-vision based tracking with a delay of less than 5\*\*ms (Walter and Couzin, unpublished results), it is possible to deliver visual stimuli that are adjusted for the animal's current position and velocity.

**Objective 3**: Use fish schools to characterize distributed conflict resolution

Using strategies outlined in objectives 1 & 2, it will be possible to direct large schools of fish into uncommon configurations. The strategy may be further enhanced using live, closed-loop tracking of large fish schools. Due to technical limitations, it may not be possible to track large ( greater than 200) groups of animals in real time. However, it may suffice to track sub-global features of the fish school, such as local speed, polarity, or density of the group. These features alone can be used to optimize a visual stimulus to deliver the desired effect on group behaviour.

**References**

Berdahl, A., Torney, C.J., Ioannou, C.C., Faria, J. & Couzin, I.D. (2013) Emergent sensing of complex environments by mobile animal groups, Science 339(6119) 574-576.

Durrant-Whyte H, Henderson TC (2008) Multisensor data fusion. In: Springer Handbook of Robotics (Siciliano B, Khatib O, eds), pp 585–610. New York: Springer

Ioannou, C.C. (2016) Swarm intelligence in fish? The difficulty in demonstrating distributed and self-organised collective intelligence in (some) animal groups, *Behav. Process*. http://dx.doi.org/10.1016/j.beproc.2016.10.005

Shadlen, M.N., and Newsome, W.T. (1996). Motion perception: seeing and deciding. *Proc. Natl. Acad. Sci.* USA 93, 628–633.

Shapiro, A.H. (1962) Bath-Tub Vortex. *Nature*. 195, 1080-1081.

Zhang, W., Chen, A., Rasch, M.J., Wu, S. (2016) Decentalized Multisensory Information Integration in Neural Systems, *J. Neurosci.* 36(2):532-547.