Achieving cohesive and mobile groups using simple sensory feedback

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Declaration of own work

I declare that the work within this thesis was carried out in accordance with the requirements of Aberystwyth Universities Regulations and Code of Practices for MPhil Research Programmes, and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others is indicated as such. Any views expressed in the dissertation are those of the author.

James Strong, April 11, 2022

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Abstract

Biological swarms use emergent behaviour to perform complex tasks with minimal resources. Research has shown that local interactions among neighbours leads to emergent behaviour. However, many questions remain unanswered on how groups can conduct successful collective motion under challenging environmental conditions, competing priorities, and in heterogeneous groups. A full understanding of this process may unlock potential solutions for computational, robotic, and biological problems. We propose a novel behaviour selection algorithm that enables agents to stay in coherent groups while navigating challenging environments. We evaluate our model, using a three-dimensional simulator, in obstacle-free and obstacle-filled environments. We measure the model's performance in two main ways, it's ability to create single cohesive groups, and it's ability to create groups that explore efficiently. We find that our model performs, at least, 18% better than similar models from the literature. We find our model is robust to increases in group size, obstacle density, and speed. Our model requires fewer computational complexities than many similar models, and as such, with further development we believe it has potential to be implemented as an effective multi-robotic platform providing efficient collective motion from low-cost individuals.

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1 Introduction

Researchers often observe biological groups performing feats outside of the individual's scope or capability [1] [2] [3]. Fully understanding how to create a whole that exceeds the sum of its parts has clear benefits for any system when considering performance or efficiency. It has been suggested that harnessing the emergent properties of swarms could generate novel solutions for computational [4] [5], robotic,[6] [7] and biological problems [8]. As robotic technologies become more readily available, an opportunity arises for multi-agent systems that could offer potential solutions in transportation, high-risk exploration, or search and rescue.

Swarming behaviour is common in nature, and certain manifestations are easily observed (e.g., shoals of mosquitofish[9] or murmurations of starlings[10]). Due to the level of synchronisation in these groups an observer may assume that there is a single omniscient force orchestrating all members of the group. However, it has been demonstrated that complex behaviours can emerge from simplistic rules of interaction among neighbours [11] and that effective groups do not require any leaders to function [12]. While swarming is ubiquitous in nature, a complete understanding of the underlying rules is far from complete. The natural world consists of many layers of interaction, each having its own properties and complexities, that make it difficult to extract the rules that connect individuals. Add to this, the obscured internal motivations of individuals and the difficulties of working with biological agents, and it becomes clear why extracting certainties about how swarms operate can be challenging.

Researchers have approached this problem by utilizing models; from the earliest attempt of simulating flocks for animation [13], through to implementing deep attention networks to model the collective behaviour of fish [14]. Initially theoretical models dominated research, but as experimental and analytic techniques improved, models based on biological data became more common, most recently, we observe an increase in the number of approaches using artificial intelligence.

In this thesis we will create and evaluate a novel set of interaction rules designed for collective motion. Our main aim is for our method to achieve cohesive and mobile groups in obstacle filled environments. We will explore which variables in our model are significant, and how their adaptation impacts performance. Our model design intent was to maximise simplicity (i.e., simplistic behaviours, simplified decision making) and minimise resource need (i.e., low range sensors, fewer neighbours considered). Wherever possible, we used biological examples to generate variable values. We believe that a model that takes this route will have the potential to reveal underlying rules previously obfuscated by complex systems, be adaptable into low-cost robotic implementations, or become a credible tool for inferring how biological agents may solve collective motion. It is important to understand how our model performs against other similar models so we will compare and evaluate our model against others similar models from the literature.

1.1 Research questions and objectives

> Develop a novel behaviour selection model that allows collective motion from simple sensory feedback.
>
> How does our model's major variables influence its performance?
>
> How does our model's performance compare against other similar models from the literature?
>
> Design our model with a level of simplicity and biological inspired variables such that the model could be used to inform our biological understanding and guide future implementation of robotic platforms.
>
> Under what conditions is our model successful? How robust is our model to challenging conditions?

1.2 Main findings, outputs and summary of work

1.2.1 Findings

> We find that simple sensory feedback is important for maintaining high levels of cohesion and mobility during collective motion. Informed groups (agent's that gather the knowledge of their number of close-range neighbours) perform, at a minimum, 18% better in coverage performance than the highest performing uninformed groups.

We find that swarm traversal in obstacle dense environments is a challenge and an under-represented area in the literature. In an obstacle-filled environment our model was able to outperform the coverage results from Couzins et al. model [15] by a minimum of 21% and Ballerini et al. model [10] by a minimum of 35%.

We find that models that focus on orientation alignment, while strong in open spaces, are unsuccessful in object filled environments.

We find that our model has an optimal speed of 4.5 body lengths, BL, per second, after which, performance begins to break down.

We find our model is able to be simpler in terms of computational complexity while outperforming comparative modelling approaches.

1.2.2 Outputs

PLOS computational biology paper in preparation

3D Agent simulator

Python Scripts for analysing 3D behaviours

Conference poster presentation ASAB Konstanz (2019)

Conference on-line poster presentation SICB (2020)

1.2.3 Summary of work

Work conducted:

Adaptation of an existing simulation framework to suit our experimental needs. This involved writing agents, obstacles and data capture into the simulation as well as the removal of elements that were not required. The most significant coding required for the functionality of the agents included behaviours, sensors, collision checking, movement and neighbour classification. All files were written in C++.

Creation of a framework to run analysis and created visual representations of the captured simulation data. The simulation data consists of agents position, heading angle and behaviour selection for every timestep. When considering this data over multiple variables, for hundreds of trials and for hundreds of agents the data points can run into the millions. To handle and make sense this large amount of data we designed a series of scripts to convert it into a useful format. The most significant scripts were converting and pre-processing data, calculating number of clusters and cluster size, calculating the speed and coverage of the largest cluster and calculating collision rates. All scripts were written in Python.

Creation of shell scripts to automate the running and organisation of experiments. This was necessary when our search-space was large and experiment numbers could run into ten's of thousands with multiple variables considered.

1.3 Organisation of the thesis

To assist in the reading of this thesis we detail the sections forthcoming, and what can be expected to be found within them. We break the continuation of this thesis into the following four sections.

Chapter 2 - Background: We explore our motivation for conducting this research and how this supports our long-term research goals. We then present our literature review detailing the research used to create and evaluate our model. We identify areas of research we feel are under-represented and illustrate how our research attempts to reconcile this. To finalise chapter two, we summarise the major multi-agent simulators available to us, and explore the limitations and benefits of us using a custom-built environment.

Chapter 3 - Research Methodology: We detail how we generated our model and how we conducted our experiments. We provide a comprehensive account of how we represent the individuals of our swarm and the interaction rules between them. We explain how our environmental conditions are set and then we justify each experiment's parameters. We complete this section explaining the data we extract, the analytic methods we used, and how we represented our data. Finally, we provide details on how we prove statistical relevance for our results.

Chapter 4 - Results: We present and give context to the findings for all proposed experiments. We include figures to visualise the findings.

Chapter 5 - Discussion: We evaluate the results and explain how they comply or contrast with the literature. We explore our results through the lens of multi-agent robotic platforms and animal behaviour. We then consider the limitations of the work and detail opportunities to improve it. Finally, we address future work, some that has already been undertaken, and some that constitutes our future plans.

2 Background

2.1 Motivation

Collective motion has been studied in a wide variety of biological systems such as fish [15] [16], insects [17] [18] [19], and birds [10] [20]. The common biological advantages found are predator avoidance, improved foraging and effective migration[21]. In each case, the exact methods and motives behind each form of co-operation might be distinct, but with the highly diverse range of agents involved (i.e., environment and agent cognition) we could assume that there will be an overlap in the process. It would seem unlikely that every species that performs some version of collective motion has arrived at that result through completely independent means. Therefore, we expect to be able to implement simplistic models using simplistic behaviours to achieve effective collective motion. We hope by implementing our model in this manner we will ensure biological plausibility, and computational efficiency for robotic platforms. This approach would still allow for subsequent increases in the model's complexity to improve performance if needed.

To design our model and understand its place in the literature, we look at research related to collective motion; more specifically but not exclusively to those related to fish schooling. We focus on the following factors,

How agents are modelled. We will examine how an agent's field of view is represented in terms of range, shape, and blind spots. We will consider body shape and simulation representation. We will consider what sensing ability is given to individuals and how it is implemented. We will explore the behaviours that agents can use (e.g., avoidance, attraction) and how each behaviour is achieved.

Which variables are significant (e.g., group size, speed, turning rate). We consider what variables are commonly explored and how they may be useful to our model.

How group performance is evaluated. We examine what performance metrics are implemented, and in what way they are effective. We investigate the methods used to capture these metrics and consider if they are relevant to our model.

Findings related to emergent properties of collective motion.

We consider any findings that reveal details about how groups move around in space.

2.2 Literature review

The first attempt at modelling swarm behaviour with actor-controlled rules was developed by Craig Reynolds in 1987[13]. Reynolds' primary interest was from an animation perspective; he was interested in achieving visually effective flocks to reduce the workload of animating individual actors. He designed independent actors who followed a rule set to achieve visual flock-like behaviour. To paraphrase his rule set (in descending order of importance): actors avoid collisions with neighbours, actors match velocity with neighbours, actors attract to the flock centre. It is important to note that no attempt is made by agents to match the orientation of neighbours. Orientation becomes common in later models, however, it is still an unsolved questions about how significant orientation alignment is in swarms. Reynolds raises some important discussion points, namely, how the perception of actors could be modelled, and how many neighbours an actor requires to be effective, given that it is not feasible to interact with every member of the population. Reynolds also introduces the concept of environmental obstacles and how taking the average of conflicting behaviours could result in an issue, when that average places agents on a collision path. Although these factors are drawn upon, no clear attempts are made to answer any specific questions. Reynolds admits that "it is difficult to objectively measure how valid these simulations are", which we concluded is not surprising, as his approach was that of animation, and as such, he desired an aesthetically pleasing swarm not necessarily a swarm, that could be tested for effectiveness to any other measures.

Huth & Wissel [16] developed a model to explore fish schooling. They concluded that fish have to take into consideration more than a single neighbour to show the "typical characteristics of a real fish school". They tested the number of nearest neighbours considered up to a maximum of four neighbours. Their implementation relies on spherical zones identifying and classifying neighbours in repulsion, parallel, attraction and search areas [fig.1]. They use four distinct behaviours, collision avoidance, search, attraction and parallel orientation (an additional behaviour compared to Reynolds[13]). The performance metrics they consider are polarisation (a measure of how directionally aligned all agents are) and the nearest neighbour distance, NND.

This model is in 2-D and did not address what impact moving to a 3-D model might have on results. Huth & Wissel focus on two different methods for decision making: Average(A-model) and Decision (D-model). A-model takes the arithmetic average of the neighbours influence and the D-model gives the greatest weight to the neighbour in the zone of interest and then halves the weight for any subsequent neighbour. For Huth & Wissel the A-model was much more successful.

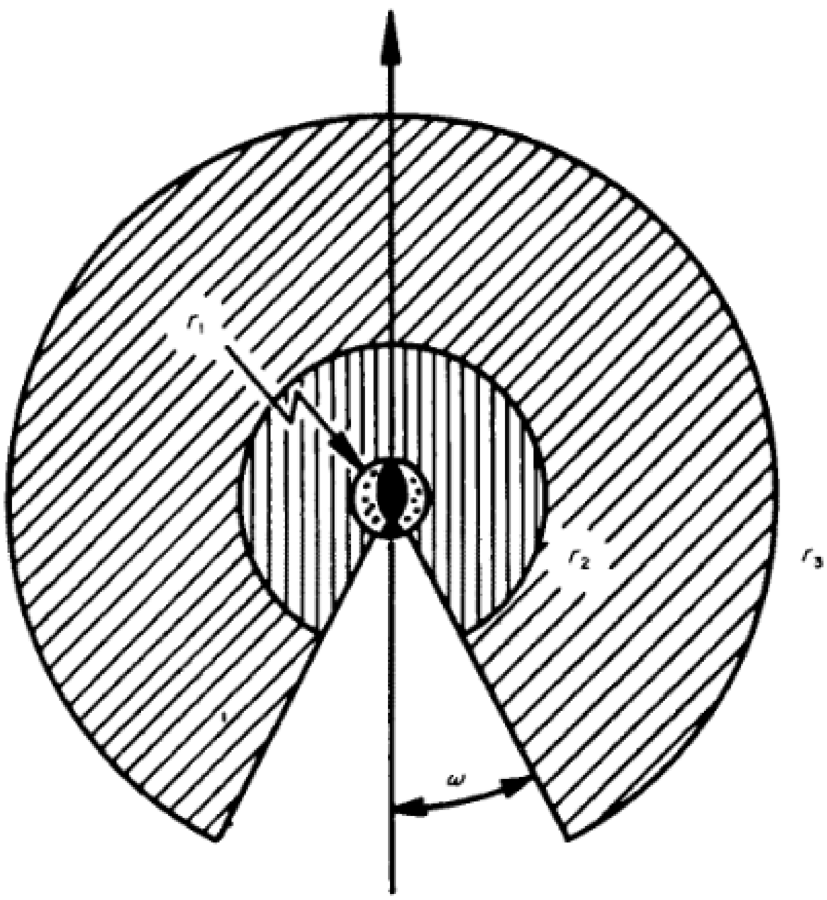

Figure 1: Huth & Wissel [16] visual representation of their model's spherical repulsion (dotted area), parallel (vertical lined area) and attraction (diagonally lined area) zones. Includes visualisation of obscured zone to the rear of the agent.

Vicsek et al.[22] introduced the idea of a self-propelled particle (SPP) model. The simple model combined a fixed velocity along with an orientation matching between particles. Vicsek recognised an alignment similarity between the results of his model and ferro-magnetism. The model they created is not biologically focused but it is important to note that Vicsek et al. do comment that SPP are much more common in biology than physics and that their findings may have more impact in a "wide range of biological systems involving clustering and migration". Most interestingly, if alignment matching manifests results comparable to ferro-magnetism, where ferro-magnetism alignment is not controlled by the individual but in fields, this may imply that alignment might not be controlled by the individual but by external conditions.

Couzins et al. [15] approach swarming as a collective behaviour problem, they show how swarms can transition between movement patterns by individuals adapting the size of their behavioural zones. In their 3-D simulation they apply three behaviours repulsion, orientation, and attraction. They use metric spherical zones[fig.2] to classify which behaviours individuals run, based on the neighbours they find in each zone. Individuals follow the following hierarchical rules: Firstly, collision avoidance is given the highest priority. Secondly, individuals are attracted to neighbours in the attraction zone and align to neighbours in the alignment zone, if neighbours are in both zones, they average the results of each behaviour from both zones. The resulting direction is used to set the agent's new heading angle. The averaging of conflicting behaviours (when behaviours suggest heading directions that do not match), whilst a common concept and conceptually simple for a reader, sets a more complex requirement on an agent; to understand and manipulate multiple behaviours. Couzins et al. use polarisation and angular momentum (the measure of how synchronised a group's turning is around the group's centre of mass) as assessment measures for their movement patterns. They found that by changing the size of zone of repulsion(zor) individuals can move location within the group. This is highly significant as it is scale-free behaviour (i.e., it does not require the individual's full knowledge of the group structure to achieve, therefore the behaviour is consistent regardless of group size). One problem with the model is that it requires no limit on the number of neighbours an individual considers when making decisions for alignment and attraction. This means the number of neighbours an individual could potentially be measuring in Couzins simulation was up to 99 and this number seems biologically implausible and computationally extravagant for individuals to calculate in dense groups.

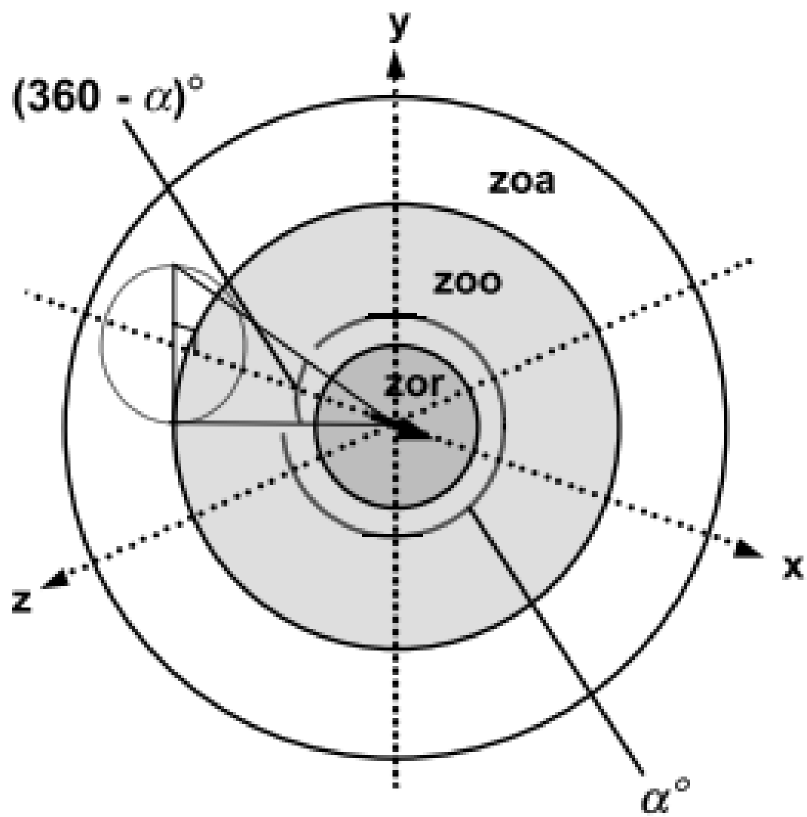

Figure 2: Couzins et al. [15] visual representation of zones of repulsion (ZOR), orientation (ZOO) and attraction (ZOA).

Kunz & Hemelrijk's [23] model explored how body size and body form influence swarm formation. Their model is implemented with three behaviours repulsion, attraction, and alignment. In this model the zones used to classify neighbours are more complicated than previous models explored. They use a 2-D model[fig.3] (their results in 3-D showed no changes) that promotes attraction to the front and alignment to the sides. They find that distribution of individuals is not homogeneous across swarms (emergent sorting) and that heterogeneity of agent size influences this (small agents tend to occupy middle of the swarm and larger agents on the edge). This model, like Couzins [15], requires no limit on the number of neighbours an individual considers.

Grégoire et al. [12] using a 2-D SPP model they were able to show that

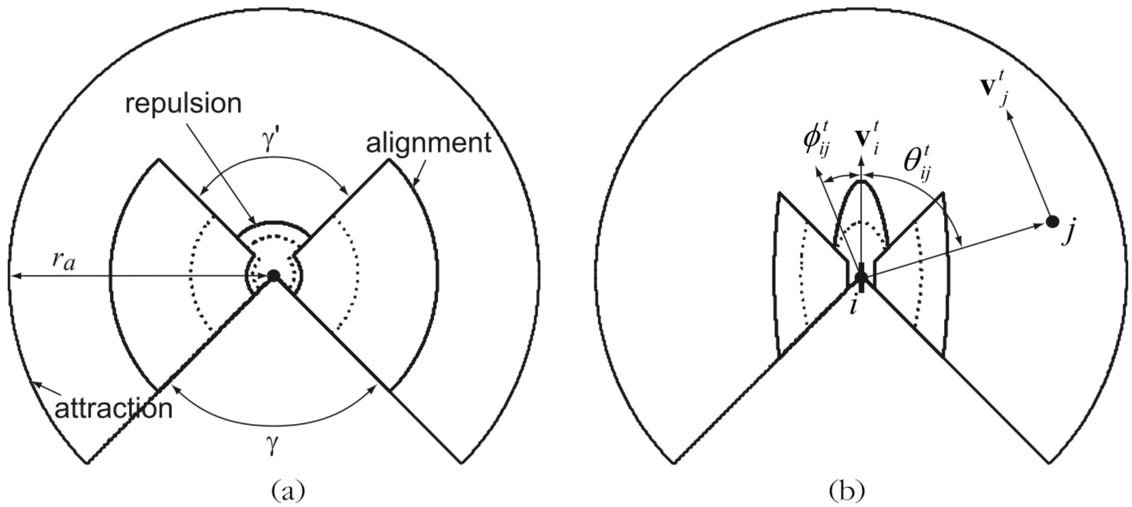

Figure 3: Kunz & Hemelricjk's [23] visual representation of their model's two implementations of asymmetric repulsion, orientation and attraction zones. Both show a wide occlusion zone but change the shape and volume of the repulsion and alignment zones.

with only local noisy alignment interactions individuals were able to maintain group cohesive motion in an infinite space. This model does not match the level of agent's complexity seen in other models but shows that alignment is successful in maintaining coherent and mobile groups.

Tien et al. [24] captured video of real fish shoals and imposed a model to fit the video data. They identified a repulsion, neutral and attraction zone [fig.4]. The neutral zone was identified as an area where neighbours have no clear influence on an individual. This discovery of a neutral zone was in contrast with existing proposed models. This method of using biological data gives an empirical view of biological swarms but may suffer from being species specific and over-fitting.

Viscido et al. 2005[25] researched the influence of group size and number of influential neighbours on individuals' movement decisions. They found both variables are important, particularly the ratio between the two values (i.e., having the number of neighbours considered smaller than the total population allows for more dynamic swarms). Viscido et al. define eight schooling metrics,

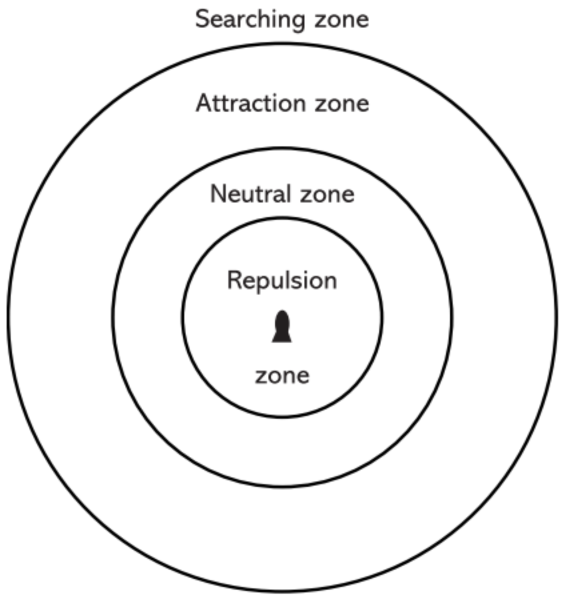

Figure 4: Tien et al. [24] visual representation of their model's spherical zones, repulsion, neutral and attraction.

- path curvature - the number of degrees of turning for each cm travelled averaged across individuals and trials.
- nearest neighbour distance.
- group size.
- expanse - the mean quadratic distance from every individual to the center of gravity for that group.
- polarisation.
- group speed - mean velocity for the centre of gravity of the group at each time point.
- stragglers - number of individuals 5+ body lengths form the nearest neighbour.
- collision rate - the mean number of agents' volumes that overlap per simulation.

which they use to assess the influences of population size and influence neighbours. Viscido et al. directly addresses the lack of direct biological data, maintaining that swarming behaviours underlying rules of interaction are still not fully understood due to this. They summarise "As a result, simulations (including our own) continue to be based more on the presumptions of their authors than on actual data".

Ballerini et al. [10] propose a topological system of neighbour selection rather than a metric system, which had been the most popular assumption up until their paper. They discovered that birds would consider 6/7 topological neighbours for decision making. They also reported topological to outperform metric in a simplistic perturbation simulation. To achieve their model, they captured stereo images of real flocks and generated 3-D representations. They were able analyse the reconstructions and generate a simple model to show that individuals need to consider only six or seven topological neighbours to maintain cohesion. Their 2-D model relies on alignment and uses a simulated predator as an external disruption. The benefits of using a topological model are evident, however, this unlimited topological distance is available for animals with little of their environment obscured. So, this could be useful for bird flocks but not possible for animals with a relatively short-range view (e.g., fish due to underwater conditions). The model they created is simplistic in the sense that the only behavioural connection between neighbours is their alignment and does not consider additional behaviours.

Cavagna et al. [26] explored scale free correlations in bird flocks by constructing a 3-D model from captured data of starlings. Scale free correlation is the ability for a swarm to have a collective response to a stimuli no matter an individual's position in the swarm or the population of the swarm. They state that scale free correlation provides agents with an improved perception as individuals can affectively leverage the perception of the entire group. Cavagna et al. make an important distinction that scale free correlation is not difficult to achieve, many simple behaviour-based rules can achieve it, but that noise is a key component in its creation. Too little noise and the group is too ordered, too much noise and the group fractures. They do note that the particular method that starlings use to achieve such high correlations eludes them. It is also important to note that they found "that two birds 1 m apart in a 10-m-wide flock are as strongly correlated as two birds 10 m apart in a 100-m-wide flock" this distance between agents is sustainable in this environment (i.e., open sky) but would not in other environments (e.g., murky water) so may not translate to other swarming animals in different

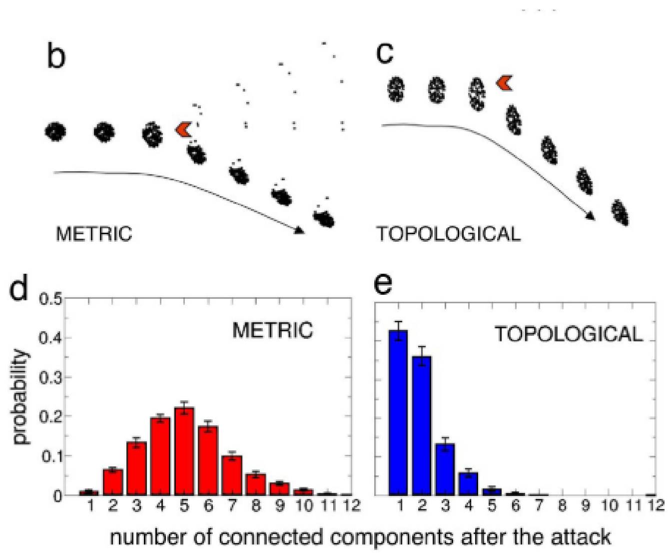

Figure 5: Ballerini et al. [10] representation of 2D model experimentation & performance of metric and topological performance under predation conditions

environments.

Lukeman et al. [20] attempt to bridge the gap left by theoretical models that use no biological data and models that use small group sizes. They did this by using a large data set to reverse engineer a 2-D interaction model. Lukeman et al. found that a metric, 360-degree, concentric circle with a weighted forward focus fit the biological data [fig.6]. Some issues, addressed in the paper, are that the data captured was from ducks swimming on top of a lake. This means that the model deals with a relatively slow movement speed. This may result in individuals who are less concerned with forward collisions and can spend more time looking behind them (resulting in the 360-degree model). This may culminate in a model that is not optimal for fast group traversal. The non-symmetrical focus is a reoccurring feature especially in models that use biological data, this preferential treatment to neighbours in directions relative to the individual makes sense when collisions from that direction would be more problematic.

Herbert-Read et al. [9] and Katz et al.(2011)[27] simultaneously conducted similar research modelling fish rules of interaction based on captured schooling data. They produced comparable results in finding that repulsion to close neighbours and attraction to distant neighbours shown in many mod-

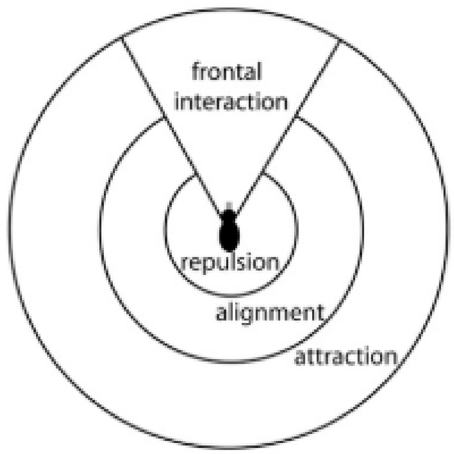

Figure 6: Lukeman et al. [20] 2D model representing an agent's repulsion, alignment and attraction zone. Including an area of focus rather than an area of occlusion

els are supported by their findings. However, both studies found that there was little proof that individuals aligned to the orientation of their neighbours and that the polarisation seen in many groups was due to a bi-directional velocity matching to agents in-front and behind combined with an attraction behaviour to neighbours who turn but only unidirectionally (those agents in-front). This lack of alignment matching was a surprising result as most models had some implementation of this behaviour within their model. Katz et al. and Herbert-Read et al. considered group size up to 30 and 8 respectively, and this model held for all group sizes tested. Both studies sited the commonly overlooked importance of acceleration in models that individuals matching and reacting to speed was an often-overlooked part of models. Both models also show evidence that individuals consider just a single nearest neighbour at a time, again going against that majority of models that consider multiple agents and take an average of their behaviours. Both papers' findings go against the grain of the established models up until this point. However, Herbert-Read et al. do not discount alignment as a possibility and point towards Radakov DV (1973) as an example of how alignment could be beneficial for predator avoidance, Herbert-Read et al. suggest the possibility of model adaptation based on situational context (e.g., a change in behaviour selection due to predation occurring).

Niizato & Gunji [28] propose a 3-D model that implements metric and topological interaction (MTI) which allows agents both options for identifying neighbours [fig.7]. They justified this as a class (metric) and collection (topological) cognition, where class can ignore individuality and look at the group as a whole, and collection will consider agents as individuals and the differences between them. The measure used to distinguish which version is used depends on how matched agents' orientation is. If they are higher in dissimilarity than the threshold then the model uses the topological version, if they are similar enough then the metric version is applied. Niizato & Gunji show that using this method of switching between metric and topological can generate internal noise that leads to scale free correlation.

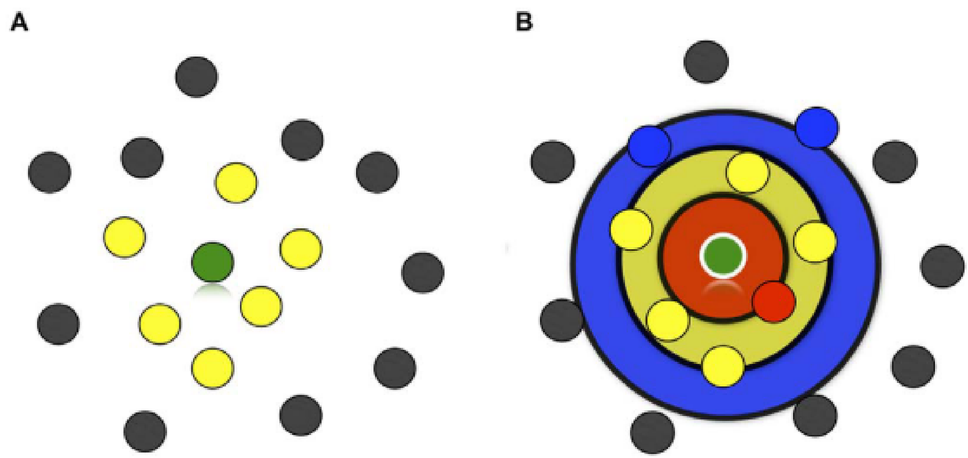

Figure 7: Niizato & Gunji's [28]model displaying topological and MTI neighbour selection

Warren 2018[29] presents a 'donut' model for collective motion in human crowds. The two areas of the donut (the ring and the hole) having differing decay rates over a metric distance for how the individual considers neighbours. The idea of sectioning a metric model this way is highly effective for Warren, however creating the model based on a observations of human interactions may elevate the required individual's level of cognition to a degree where it is infeasible for less able individuals.

Ried et al. [30] approach their model from a collective learning standpoint. Where agents can sense the environment and then learn and adapt to make decisions. They believe an approach like this removes more assumptions from the creation of individuals and leads to less over-fitting (i.e., agents are created to prove a particular behaviour at the cost of all others). This method approaches the issue of over-fitting in a unique way, but the implementation of the model is outside of the scope of this project.

Heras et al. [14] use a deep attention network to model collective motion from biological data of fish swarms. They use this method, as they claim it can be predictive in collective motion but still be not overly complex to become incomprehensible. They find that individuals can be responsive to up to twenty neighbours but can focus on as little as one or two. The number of neighbours is contextualised by the speed, direction, and position of other neighbours. They also reported that repulsion, alignment, and attraction zones had overlap which is often overlooked in previous models. Deep attention networks have been successful in multi-dimensional problems, it is possible that this method of generating interaction rules could be successful for uncovering underlying rules. A challenge remains if they are able to stay "human-readable" and not lose their context.

Li et al. [31] presented that often fish would adapt their position in a school to take advantage of environmental physical properties, namely, neighbour-induced flows. This implies that there can be many complicated layers to animal swarming than just local rules of interaction in a metric or topological model. There is the possibility that alignment might be caused from fish aligning their bodies into vortex flows that make swimming more efficient, and this would support earlier findings that positioning of individuals was not related to neighbour orientation but position. The problem with introducing findings like this into our model is that they can be very species dependent and may not translate to other swarms. One of our aims is to avoid over-fitting.

2.3 Knowledge gaps

Based on the literature review we identify four areas that we believe are under-represented and fall into the scope of our thesis.

- Three-dimensional collective motion in obstacle filled environments
- How groups stay cohesive and mobile under changing conditions

- How a groups heterogeneity of individuals can influence collective motion.

- Alternative methods to how individuals make behaviour selections between competing priorities.

Our model will focus on a single piece of sensory feedback, the number of close-range neighbours. Our model will represent a simple idea, as an individual if you are satisfied with the number of neighbours around you then your priority is exploring, if you are not satisfied, your priority is finding more neighbours. We will use our model to explore how effective this method of collective motion is. We will then proceed to test how the model reacts to changing internal and external variables compared to other models from the literature.

2.4 Multi-Agent simulators

The most recent comprehensive review of agent-based modelling and simulation conducted by Abar [32] found 86 tools available to researchers. At the time of writing, CoMSES website OpenABM [33] stores over 800 different models. There are many options, however, most of these packages fall outside our application domain or are inappropriate for the aims of our project. The following table lists simulators we investigated as platforms to create our model. Our criteria included licensing availability, language, simulated dimensions, and scope [Table.1].

We also considered creating our environment and model within a game engine. Two viable options explored were Unity[42] and Unreal[43]. The advantage this would have allowed us was the massive available libraries for physics (e.g., fluid dynamics), collision detection (e.g., continuous collision detection(CDD)) and complicated body modelling. The popularity of these engines ensures libraries have high quality support and constant development. They are designed with visualisation in mind so also hold the advantage of being highly capable of displaying simulations. The disadvantage related to this kind of product is the significant time investment required to learn.

We rejected most platforms for not having the required flexibility we needed, anticipated learn-times being too high or a software's lack of continued support. Although all the packages we explored can fulfil our simulation needs there is no benchmark software that is used commonly in the research.

Simulator	Licensing	Source code	Model dimensions	Use case
Behaviour composer [34]	open source	Java	2D/3D	Natural science social networking.
Breve [35]	open source	C++	3D	Artificial life simulations.
Bsim [36]	open source	Java	3D	Particle simulations.
DigiHive [37]	closed source	C++	3D	Simulations of artificial life and emergent phenomena.
F.L.A.M.E [38]	open Source	C	2D/3D	Large-scale, multi-purpose simulations.
GridABM [39]	open source	Java	3D	Large-scale, high-performance agent-based modeler.
Repast Simphony [40]	open source	Java	2D/3D	Complex biological adaptive systems.
Swarm [41]	open source	Java Object-C	2D/3D	Extreme-scale biological systems.

Table 1: **Simulators considered for this project**

As such, we decided to create our own, to guarantee flexibility in our experimental approach, and ensuring we could trust the results. Using our own simulator (described in the Research Methodology) also ensured we can adapt and modify the system easily and without restriction. Finally, we already had access and experience with the platform from previous work, so it added minimal additional learning time to the project. We expect to expand the platform (e.g., GUI, agent body form) in the future as we intend to continue to use it for experimentation after this project.

3 Research Methodology

3.1 Simulation Architecture

The three-dimensional multi-agent simulator was implemented in C++ with visual interface supported by OpenGL. The simulation environment was adapted from software written by Dr. Alexandros Giagkos. The software's original purpose was to simulate UAV communication networks. With Dr. Giagkos' permission we re-purposed the environment and added obstacles and self controlled agents. The simulation environment is initialised as a continuous cube volume (defined by length, l_{tank}) which contains free-floating obstacles (fixed in space) and agents. The obstacles and agents are defined as solid spheres with fixed radii, r_{obstacle} and r_{agent}, respectively.

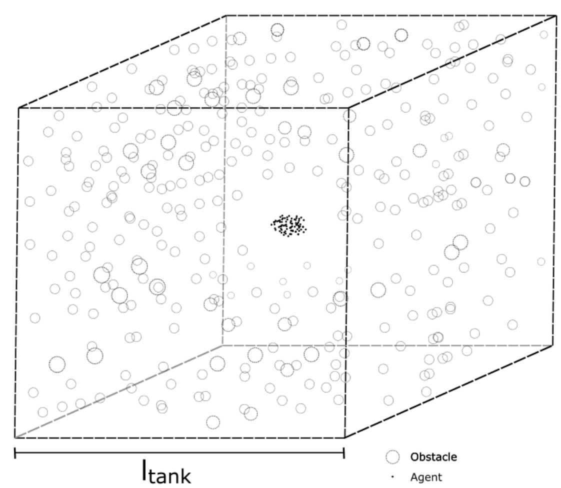

Figure 8: Simulation tank representation, displaying example of randomly placed obstacles and agents.

During testing of our simulations we discovered that our system reaches a steady-state between appropriately 4 - 6 minutes. We measured steady-state as the plateauing of the number of clusters and the size of the largest cluster. Based on this, each experimental trial runs for a duration of 10 minutes with the final 2 minutes reserved for data collection. Allowing our system to reach its steady-state, before we capture data, reduces the impact of the starting conditions upon our results.

3.2 Agents

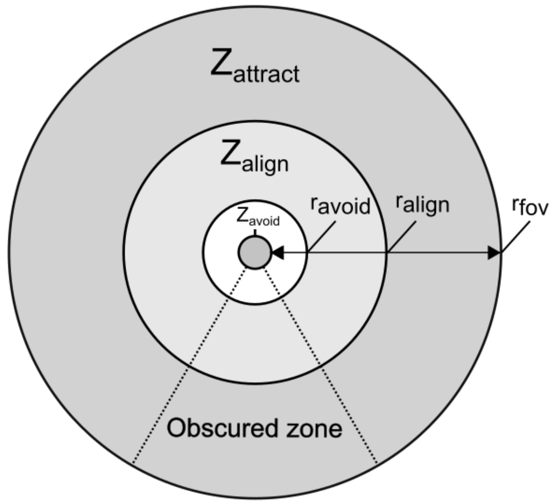

Figure 9: 2-D representation of our 3-D agent's *fov*

Agents are represented using a position vector (p $\langle$x,y,z$\rangle$), heading direction (h $\langle$ θ, ϕ $\rangle$), and speed, s. θ and ϕ correspond to the agents two degrees of freedom, heading angle in the horizontal and vertical plane, respectively. Agents can only traverse in the direction of their heading angle.

It is assumed that agents have access only to the positions and heading directions of neighbours that are within their field of view, *fov*. The *fov* of an agent is defined by radius, r_{fov} (how far the agent can see) and two relative angles (θ_{fov} and ϕ_{fov}) with respect to the heading direction. The *fov* is further divided into three non-overlapping concentric spherical zones; avoidance (z_{avoid}), alignment (z_{align}) and attraction (z_{attract}). The relative size of each zone in relation to r_{fov} is defined by r_{avoid} and r_{align}, see [fig.9]. Agents' decision making is based upon identifying neighbours within each zone. Suppose dij is the distance between agent i's and agent j's circumference, agent j would be classified in agents i's z_{avoid} if $dij < r_{\text{avoid}}$, z_{align} if $dij > r_{\text{avoid}}$ and $dij < r_{\text{align}}$, or z_{attract} if $dij > r_{\text{align}}$.

For initialisation, agents are randomly assigned co-ordinates from within the most central voxel as their starting position. Each agent is generated with a random heading direction, all agents heading directions are matched to this value $\pm$ 5° in both θ and ϕ. We initialise all agents this way to ensure our initial conditions are not influencing cluster splits. For obstacle filled environments the obstacles are initialised randomly throughout the tank excluding the central voxel in which agents are initialized to ensure the simulation does not commence where an obstacle starts in the midst of the swarm.

3.3 Model design

Simulations are run in discrete time steps t, with τ increments. The position of an agent, i, is updated according to,

$$\mathrm{p_i(t+\tau) = p_i(t) + s_i(t)h_i(t)}\tau, \tag{1}$$

where heading direction, h_{i}, is controlled by running one of the four behaviours listed below:

Avoidance behaviour prevents the agent from colliding with close-range objects,

$$\mathrm{h_{avoid}} = -\sum_{\mathrm{j\neq i}}^{\mathrm{n_{avoid}}} \frac{\mathrm{p_{ij}(t)}}{\mathrm{|\ p_{ij}(t)\ |}} - \sum_{\mathrm{k=1}}^{\mathrm{o_{avoid}}} \frac{\mathrm{p_{ik}(t)}}{\mathrm{|\ p_{ik}(t)\ |}}. \tag{2}$$

Where n_{avoid} and o_{avoid} indicate neighbours and obstacles in the z_{avoid} at time t, p_{ij} = ($\mathrm{p_j}$ - $\mathrm{p_i}$) / | ($\mathrm{p_j}$ - $\mathrm{p_i}$)| is the unit vector in the direction of neighbour j and p_{ik} = ($\mathrm{p_k}$ - $\mathrm{p_i}$) / | ($\mathrm{p_k}$ - $\mathrm{p_i}$)| is the unit vector in the direction of obstacle k.

This behaviour calculates a heading direction that maximises divergence from any obstacles or neighbours that have been detected in the avoidance zone.

Alignment behaviour allows the agent to orient itself to the heading direction of the N nearest neighbours found in the z_{align}, (n_{align})

$$\mathrm{h_{align}} = \sum_{\mathrm{j=1}}^{\mathrm{n_{align}}} \frac{\mathrm{h_j(t)}}{\mathrm{|\ h_j(t)\ |}}. \tag{3}$$

This behaviour calculates a heading direction that takes the average of its N nearest neighbours heading directions detected from within in the alignment zone.

Attraction behaviour allows the agent to move towards N nearest neighbours found in the z_{attract}, (n_{attract})

$$\mathrm{h}_{\text{attract}} = \sum_{\mathrm{j}=1}^{\mathrm{n}_{\text{attract}}} \frac{\mathrm{p}_{\mathrm{ij}}(\mathrm{t})}{\mid \mathrm{p}_{\mathrm{ij}}(\mathrm{t}) \mid}. \tag{4}$$

This behaviour calculates a heading direction to intercept the centre of gravity of the N nearest neighbours detected in the attraction zone.

Search behaviour modifies the agent's heading direction using,

$$\mathrm{h}_{\text{search}} = \theta_{\mathrm{i}}(\mathrm{t}) + \delta\theta_{\max}, \phi_{\mathrm{i}}(\mathrm{t}) + \delta\phi_{\max} \tag{5}$$

where δ is a random value between -1 and 1.

This behaviour manifests such that when an agent searches it sets a heading direction randomly from a direction that falls within its current *fov*.

Once agents have generated a heading direction we apply a constraint to limit their maximum turning angle. We designed agents with an a-symmetrical maximum turning rate in the horizontal, $\theta_{\max}$, and vertical axis, $\phi_{\max}$. When implementing new a heading direction, $h(\mathrm{t}+\tau)$, if the change in $\theta \leq \theta_{\max}$ and the change in $\phi \leq \phi_{\max}$ then we can update the current heading, $h(\mathrm{t})$, to the proposed $h(\mathrm{t}+\tau)$. If the direction heading difference is larger in the horizontal axis or the vertical axis, then we rotate the heading in the desired direction by $\theta_{\max}$ or $\phi_{\max}$ respectively. This results in agents using the horizontal plane more than the vertical plane to orient themselves to new heading directions. This reduces the tendency for agents to perform manoeuvres that result with them flipping vertically. Although there are examples of fish that swim 'up-side down' (e.g., African Catfish[44]) this is not typical and we wanted to avoid this in our simulation. By limiting the maximum turning angle we cap their turning speed to approximately 180 degrees in the horizontal per second and 90 degrees in the vertical per second. Although turning rates are species and situationally dependant this rate would be considered standard [45].

3.4 Behaviour Selection

We hypothesise that creating cohesive and mobile swarms can be approached as a behaviour selection problem. Existing research which used similar sets of

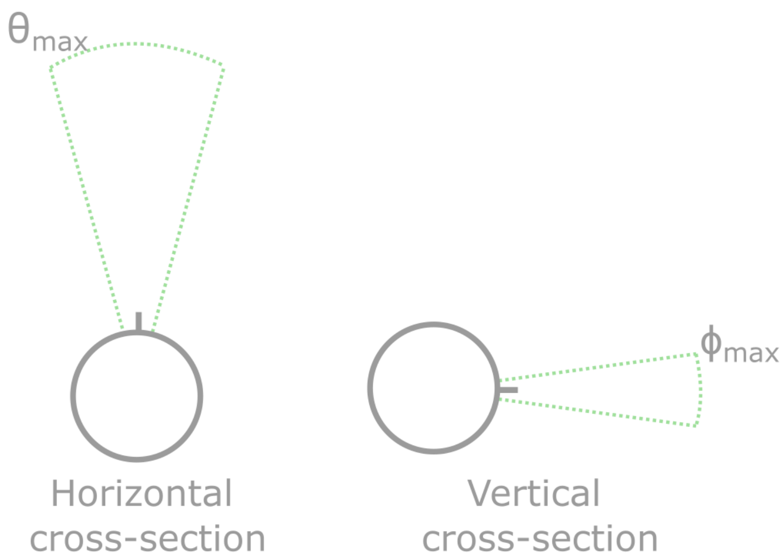

Figure 10: Visualisation of asymmetric turning restriction in horizontal and vertical planes. Zone inside dashed lines shows acceptable heading directions, if new heading direction falls outside of the zone the closest restriction boundary becomes the new heading direction

behaviours has shown that while alignment increases the mobility of groups, attraction enables them to maintain cohesion. However, these two behaviours will often calculate divergent heading angles. This issue has been addressed before by averaging the heading angles from competing behaviours [15] [16]. Here we propose an alternative method to solve this trade off, utilising timely decisions to select one single behaviour based on simple sensory feedback (n_{align}). The agent's goal is to maintain a minimum count of neighbours in the z_{align}. If this is achieved, they select the alignment(mobility) behaviour, if it is not, they choose attraction(cohesion) behaviour.

The behaviour selection process is hierarchical (Algorithm 1) with avoidance and search behaviours having the highest and lowest priority, respectively. While avoidance behaviour ensures safety, search is activated only when there are no neighbours in the *fov*. If there are no neighbours or obstacles in the z_{avoid}, the agent chooses between alignment and attraction behaviours using a logistic function

$$\mathrm{P_{align}} = \frac{1}{1 + \mathrm{e}^{-K(\mathrm{n_{align}} - \mathrm{M})}} \tag{6}$$

which calculates the probability of selecting alignment behaviour, p_{align}, based on the number of neighbours found in the z_{align}, n_{align}. p_{align} increases non-linearly with the increase of n_{align} (sigmoid curve) from the range of 0 (100% attraction) to 1 (100% alignment). The variables M and K are the inflection point and growth rate of the sigmoid curve, respectively. With M controlling the likelihood of the agent selecting the alignment behaviour; p_{align} increases with decreasing M (100% when M=0). K determines randomness in behaviour selection. If K=0, p_{align} is 0.5 resulting in equal probability of selecting either behaviour. [Fig.11] is a visualisation of this function.

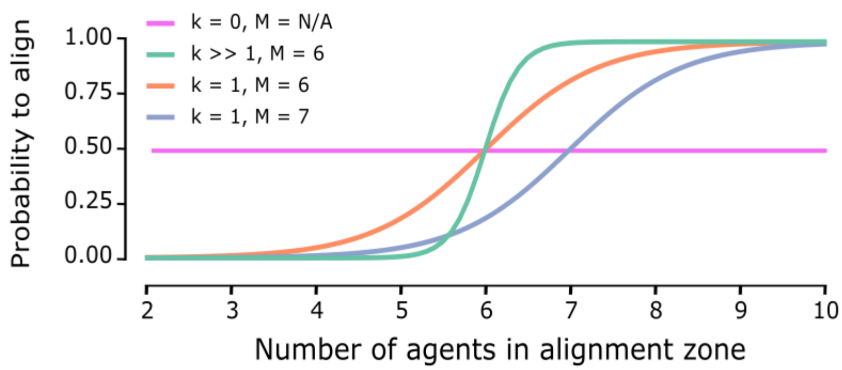

Figure 11: Figure showing the influence of M and K on calculating $\mathrm{p_{align}}$

Algorithm 1: Behaviour Selection

```
Result: h (new heading direction)
Inputs: positional data of agents and obstacles
if agent or obstacle detected in z_avoid then
    h = h_avoid;
else if agents detected then
    if agents only in z_align then
        h = h_align;
    if agents only in z_attract then
        h = h_attract;
    else if agents in z_align and z_attract then
        Calculate p_align;
        R = rand(0,1);
        if R > p_align then
            h = h_attract;
        else if R < p_align then
            h = h_align;
        end
    end
else if no agents detected then
    h = h_search;
end
```

When $K \gg 1$, the function simplifies into a conditional statement,

$$\mathrm{p}_{\mathrm{align}} = \begin{cases} 1 & \text{if } n_{align} > M \\ 0.5 & \text{if } n_{align} = M. \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Research shows that logistic functions have been successfully applied to behaviour selection problems in multi-agent systems [46] and have proved an accurate model for describing the decision-making process observed in real animal groups, specifically in decisions between two distinct options.

In situations where agents can detect only neighbours in the z_{align} there is no selection to make, and they run the alignment behaviour. Similarly, when neighbours are only found in z_{attract} they run the attraction behaviour. A visual representation of examples of behaviour selection can be seen in [fig.12].

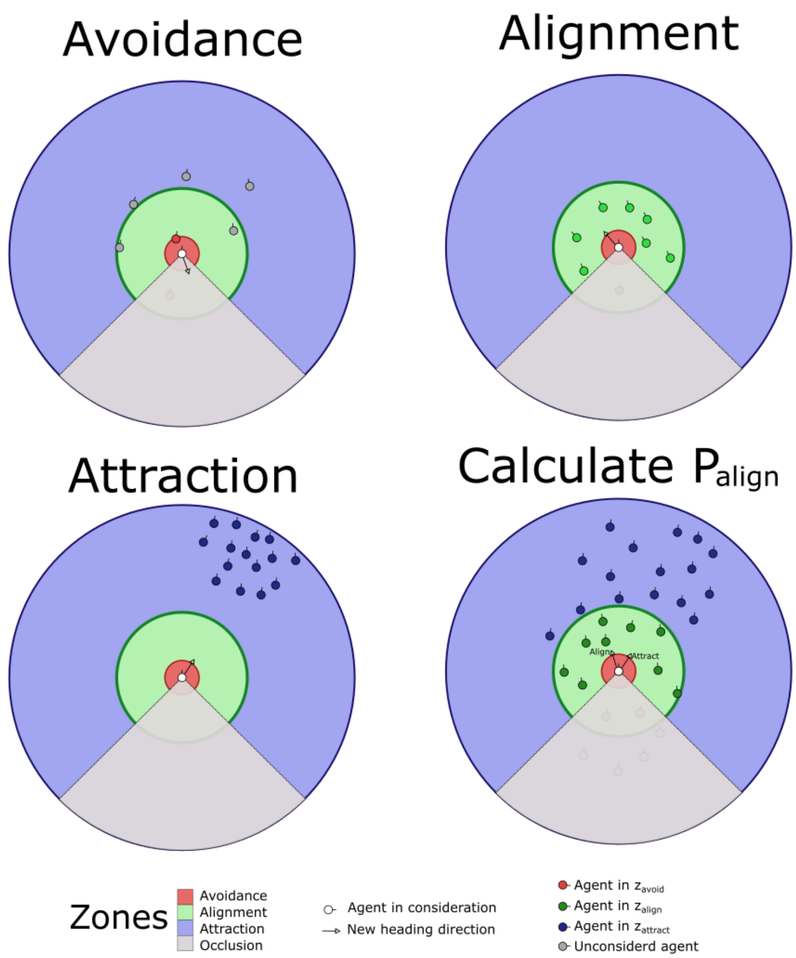

Figure 12: Visual representation of how neighbour placement influences behaviour selection (2D projection). Top left: Neighbour inside avoidance zone; avoidance behaviour selected. Top right: All neighbours in alignment zone; alignment behaviour selected. Bottom left: All neighbours in attraction zone; attraction behaviour selected. Bottom right: Neighbours inside alignment and attraction zone; Calculate P_{align} selected.

3.5 Experimental Design

3.5.1 Physical restrictions

When new positional vectors are calculated for agents, we do not permit changes in position that would result in agents, obstacles or tank walls intersecting (i.e., collisions). We resolve these situations by ignoring the proposed positional change. We consider these ignored movements as collisions and track the collision rate for each trial.

3.5.2 Variables

A full list of significant variables can be found in [Table.2]. It shows the most typical set up for trials unless otherwise stated in the experiment details.

Table 2: **Experimental Variables**

Parameter	Symbol	Units of measurement	Values
Agent			
field of view	θ_{fov}, ϕ_{fov}	degree	270
avoidance radius	r_{avoid}	L	4
alignment radius	r_{align}	L	10*
fov radius	r_{fov}	L	24
speed	s	L s^{-1}	6*
agent radius	r_{agent}	unit	1
Simulation			
obstacle radius	r_{obstacle}	L	5
obstacle density	$\mathrm{d}_{\text{obstacle}}$	% of total environment	2
tank length	l_{tank}	L	335*
Experimental variables			
preferred neighbours in zalign	M	n/a	10*
logistic growth rate	K	n/a	1*
number of neighbours considered	N	n/a	g-1*
time step increments	τ	seconds	0.1
group size	g	n/a	200*
horizontal turning rate	θ_{max}	degree s^{-1}	180
vertical turning rate	ϕ_{max}	degree s^{-1}	90

* unless otherwise stated
2L = agent body length (BL)

Our variable selection for field of view simulates a wide vision range with an area of occlusion directly behind the agent. This was inspired from work by Pita et al.[47] and their research into fish field of view and similar fov implementations from the literature [15], [16]. Our value for r_{avoid} was selected based upon the findings of [9] that observed 1.5-2 body lengths to be a typically maintained distance between individuals. Partridge & Pitcher[48] present the hypothesis that fish use their lateral line for close range orientation and their vision for longer range attraction. Therefore, the value for r_{align} was selected as relatively low value to represent this sensor type. It also reflects our belief that identifying a neighbour's orientation is an easier task to perform at closer ranges. The value for r_{fov} was selected to represent a long-range identification method (i.e, vision) but still somewhat limited to reflect the medium (i.e, reduced visible range for underwater due to turbidity). The values for speed and turning rate are based on [45]; it is important to note that while we do not represent a specific species, we have aimed to chose variables that would comfortably fall within realistic ranges based on animal type and body length. Obstacle radius was selected as a size large enough to alter heading direction, we found that smaller obstacles did not interrupt swarms. M values range from 0 - 20. Calculating an accurate maximum number of agents that can fit inside an agents z_{align} is a considerable problem [49]. We used Mhallah's work [49] to estimate an appropriate value and then confirmed by testing to see the highest reported number of agents seen inside an agents z_{align} over a 100 minute trial. The combination of these resulted in our maximum 20 agents, however as covered in later sections we could have reduced our range slightly as we found an agent achieving above 16 neighbours regularly was rare. Wherever possible, the selection of these variables are inspired by observations in nature or common practice in other models from literature. We aimed to maintain a level of biological plausibility without over-fitting to a specific species.

3.6 Experiments

Table 3: **Experiment listings**

Experiment no.	Description	Design (section)	Results (section)
1	Comparison of 5 model variants	3.6.1	4.1 - 4.1.4
2	How N influences performance	3.6.2	4.2
3	How M & K influence performance	3.6.3	4.3 - 4.4
4	How do informed decisions influence performance	3.6.4	4.5
5	How does speed influence performance	3.6.5	4.6
6	How does group size influence performance	3.6.6	4.7
7	How does obstacle density influence performance	3.6.7	4.8
8	How does ralign ratio influence performance	3.6.8	4.9
9	How does heterogeneity influence performance	3.6.9	4.10

3.6.1 Comparison of five behaviour selection variants

Our model design focuses on the idea that controlling the number of close-range neighbours is important to collective motion. To explore the validity of this idea we used equation 1 to create four behaviour selection variants to begin to understand how the parameters M and K influence group performance and the results that can be achieved within the bounds of our model. We created 4 variants: 1) Align (M=0, K=4), 2) Probability-based (M=10, K=2), 3) Attract (M = 20, K =4) and 4) Coin flip(K=0), full comparison of variants can be found in Table[4]. Among these, the Probability-based variant is the only one which negotiates between attraction and alignment behaviours based on n_{align}. The other two (Align and Attract variants) are chosen as the extremes in behaviour selection against which the performance of the Probability-based variant can be evaluated. Agents running the Align variant will always select the alignment behaviour if there is at least one neighbour in the z_{align}. Similarly, agents running the Attract variant will always select the attraction behaviour as maintaining 20 neighbours in the z_{align} is rare. Coin-flip does not require an M value as when $K = 0$ $p_{\text{align}} = 0.5$ so there is always an even chance of either alignment or attraction behaviour being selected. Using these four variants we aim to start understanding the range of behaviours available to our model. We hypothesize that the Probability-based variant will be successful, as it will select attraction when it needs more neighbours and alignment when it has neighbours and wants to be mobile. We also include an additional Control variant: 5) for the Control variant the heading direction is calculated by taking the average of both directions proposed by alignment and attraction behaviours. This method of averaging the two is taken from the literature Couzin et al. [15] and was fully explained in the background section. This allows us to compare our model (using a single behavioural choice) against a classic model (using an average of behaviours).

Table 4: **Variant variables and their influence on Palign**

Variant	**M Value**	**K Value**	**N Value**	$\mathbf{P_{align}}$
Align	0	4	g-1	1
Attract	20	4	g-1	0
Coin flip	n/a*	0	g-1	0.5
Control	n/a**	n/a**	g-1	n/a
Probability-based	10	2	g-1	Depends on n_{align}

* Coin flip's M value is irrelevant when K = 0 as P_{align} is always 0.5
** control does not use the logistic function to calculate behaviour selection it averages attraction and alignment behaviours at every time-step.

3.6.2 What is the minimum n_{align} and n_{attract} needed to maintain performance?

Previous research suggests that when an agent is making a decision it is sufficient to consider only a small number of neighbours [16] [10]. This encouraged us to evaluate if the same principle can be applied to our simulation framework: i.e., once a behaviour is selected (either align or attract), what is the minimum number of neighbours needed to calculate a heading direction that maintains a good group performance? We addressed this question by first comparing our variants, but this time with the number of neighbours considered as six agents. We then explored varying N between 1 and 12, with increments of 1, to begin to understand the relationship between N and individual variants' performances.

3.6.3 How does M and K impact performance?

After creating four discrete variants of our model we decided to evaluate further how the full range of M and K impact performance, we first varied M between 0 and 20 with increments of 2 (in these experiments, we set K = 2). We then varied K between 0 and 4 with increments of 0.2 (in these experiments we set M = 10). We believed that adaptation of M and K could result in differing levels of cohesion and mobility.

3.6.4 Comparing informed versus uniformed decisions

The coin-flip variant is an uninformed variant, this means behaviour selection is not dependant on the $\mathrm{n}_{\mathrm{align}}$(i.e no matter the value of n_{align}, $p_{\mathrm{align}} = 0.5$). We want to know how significant it is for individuals to be informed (i.e., making their decisions based on n_{align}). Is the ratio of p_{align} driving performance or are the timely decisions by the informed variant improving performance? To address this question, we run simulations for pre-set uninformed $\mathrm{p}_{\mathrm{align}}$ values in the range 0 - 1 with increments of 0.1, essentially removing the agent's ability to react to n_{align}.

3.6.5 Speed

All previous experiments have been conducted with a constant speed (6 body lengths per second), to assess how robust our variants are to the differing speeds we explore the in the range from $3L$ s^{-1} to $15L$ s^{-1} with incremental steps of $3L$ s^{-1}.

3.6.6 Group size

To maintain the density of the agents (number of agents divided by volume of tank), the tank is scaled with the number of agents for a given trial. To calculate the tank dimensions, we first approximate the minimum voxel size required to contain all agents spaced by z_{avoid}. Once we have generated this cube, we multiply it by ten in all dimensions to achieve the final tank.

All previous experiments have been run with a constant group size (200 agents), to assess how robust our variants are to differing group sizes we explore the following range of group sizes 50, 100, 200 and 400. Our motivation for altering group size was to explore how well our model scales with group size.

3.6.7 Obstacle density

Obstacle density is scaled with the volume of the tank to maintain a constant obstacle density. All previous experiments have been run with a constant obstacle density 1% or without obstacles. To assess how our variants perform under differing obstacle densities we explore densities of 0.5%, 1%, 2%, 4% and 8%. In [Table.5] we show how obstacle density manifests as the average distance between obstacles in our simulation.

Density	Label	Average distance between obstacles
0.0%	$d_{\text{obstacle0}}$	N/A
0.5%	$d_{\text{obstacle1}}$	25BL
1.0%	$d_{\text{obstacle2}}$	20BL
2.0%	$d_{\text{obstacle3}}$	16.5BL
4.0%	$d_{\text{obstacle4}}$	13.5BL
8.0%	$d_{\text{obstacle5}}$	12 BL

Table 5: **Obstacle density and average distance between obstacles**

3.6.8 How does the ratio between $\mathbf{z_{align}}$ and $\mathbf{z_{attract}}$ impact the performance of the variants?

For all previous experiments r_{align} has been constant, and as such the volumes of z_{align} and z_{attract} also do not change. Research has proposed that fish may utilise alignment behaviour using their lateral-line (close-range) and attraction behaviour using vision (long-range)[48]. We believe it is reasonable that as the distance between agents increases so does the difficulty to match alignment accurately. Therefore, we selected a close-range z_{align}. Our z_{align}

sizing limited the number of agents that could fit within the zone, this established the range of from M = 0 (complete alignment) to M = 20 (complete attraction). By changing the size of r_{align} we increase the number of agents that can fit inside this zone and make lower values of M easier to satisfy. To understand what influence the changing volume of z_{align} has over performance we modify r_{align} in the rage of 10 to 18 with incremental steps of 4. We do not alter r_{avoid} or r_{fov} so the maximum range of an agent's *fov* and the volume of the Z_{avoid} does not alter. These changes manifest as increasing the range an agent can identify orientation in its neighbours, increasing the zone size that an agent considers its neighbours 'close' whilst maintaining the overall fov size.

3.6.9 Exploring heterogeneity

For all previous experiments we studied homogeneous groups that consisted of identical agents. In robotics, this is not the case [50]. To begin to understand how group heterogeneity may alter group performance we explore two simple implementations. Firstly, we take two unique variants (a: Align and b: Probability-based) and assign them to individuals. We control the ratio between the two variants across the whole swarm, from 0 (100% variant a) to 100 (100% variant b) with incremental steps of 10%. This is to simulate a swarm containing a mix of individuals from each variant a and b. Secondly, we explore the same two variants, this time each agent can change its state between variant a and b and the ratio is now used to control the probability of an agent choosing a variant. This is designed to simulate an agent tending to decide its internal state between the two variants. Again, we control the ratio between the two variants from 0 (100% chance of choosing variant a) to 100 (100% chance of choosing variant b) with incremental steps of 10%.

3.7 Data Analysis

All simulations were repeated 100 times (i.e., trials). For each trial we captured data only from the final two minutes at a sampling rate of 1hz, once the simulation had reached a steady state. The data analysis was performed off-line using custom written python scripts.

3.7.1 Captured data

For each captured frame we log agents' positions and heading angles, number of neighbours found in the z_{avoid}, z_{align} and z_{attract} and behaviour selections. We also record the positions of obstacles for each trial. In addition, for each experiment we generate a meta file detailing all experimental variables. All files are saved in a csv file format.

3.7.2 Group performance metrics

We measure group performance using two metrics: cohesion and mobility. In an ideal scenario agents stick together and move freely within their environment. However, agents often split into smaller groups (i.e., clusters) when they are avoiding collisions (e.g., obstacles). These splits can be even (e.g., two similar sized clusters) or uneven (e.g., one large and multiple small clusters). To account for these variations, we evaluate cohesion using two measures: number of clusters and the number of agents in the largest cluster (represented as a percentage of the group size). To detect clusters, we wrote a modified DBSCAN algorithm [51]. In our implementation we assume that: 1) one agent is enough to form a cluster and 2) a new cluster is formed when agents from the new cluster do not have an intersecting *fov* with agents from the existing cluster. The higher the number of clusters or the smaller the largest cluster size, the less cohesive the group is. Achieving very cohesive groups can come at the detriment of movement, so we use two measures to evaluate mobility: speed of the largest cluster and coverage, the number of unique voxels discovered. Speed is calculated as the instantaneous velocity of the largest cluster's centre of gravity. Coverage is calculated as the percentage of voxels discovered by atleast 30% of the group. The higher the speed the more mobile we consider groups. Coverage indicates the level of mobility and cohesion so we use it as our major performance indicator.

3.7.3 Group emergent properties

To understand better the underlying mechanics that control group performance we calculate the polarisation, angular momentum, the behaviour distribution of the largest cluster. Polarisation indicates how aligned agents are in respect to neighbours and angular momentum indicates how well the group can synchronise turns. These measures have been used in the literature to analyse swarm behaviour [15], [25]. Behaviour distribution we developed to measure the ratio of avoidance, attraction and alignment behaviours selected by a variant across full range of trials.

3.7.4 Statistical tests

We ran one way analysis of variance (ANOVA) followed by Turkey Kramer multiple comparisons test to compare the coverage performance of the five variants at a significance level of $p \leq 0.05$. We did this to ensure that we could confidently report statistical significance between the results we found when comparing variants. ANOVA was used to first assess differences between the five variants as a group, then Turkey Kramer was used to assess statistical difference between each set of pairs.

4 Results

4.1 Comparison of variants (Experiment 1)

We conducted the comparison of the five variants([table.3]) under two different conditions. First, we set the number of neighbours considered for heading direction calculations to allow the maximum neighbours possible (N = G-1). Then we ran the same comparison but with six neighbours (N = 6). All results for coverage showed statistical difference to $p \leq 0.05$, except for the comparison between Coin flip and Control under N = 6 conditions where there was no statistical difference between the coverage results.

4.1.1 Maximum neighbours (N = G-1) (Experiment 1)

The Align variant is the best performing in obstacle-free environments. However, it drops 65% in performance when placed into an obstacle-filled environment. This break-down in performance stems from a loss of cohesion; a 50% drop in largest cluster percentage and a 6 cluster increase in the average number of clusters; seen in [fig.13a and b]. Irrespective of obstacles, the Align variant is able to maximise its speed under both conditions [fig.13c] proving itself a highly mobile variant.

The Attract variant is the worst performing variant in both environments at least 45% worse in coverage than the next worst variant. This is due to the variant being highly cohesive but very immobile. These features also result in the Attract variant seeing no change in performance when placed in an obstacle-filled environment, as the number of obstacle encounters is minimal. When considering all the variants shown in [Fig.13], the Attract variant has the highest cohesion. It achieves the highest largest cluster percentage, 100%, and the lowest number of clusters possible, 1. However, this high cohesion is at the expense of speed, making Attract the slowest of all variants.

In terms of coverage, the Probability-based variant is the best performing variant in obstacle-filled environments, and the second best in obstacle-free environments. The Probability-based variant is able to combine the cohesive ability of the Attract variant and the mobility of the Align variant. It achieves the second fastest speed whilst simultaneously achieving a high cohesion.

Unexpectedly, the results show that the Coin-flip variant outperforms the Control variant. The behaviour selection difference between the two variants is that Control combines the heading directions of alignment and attraction

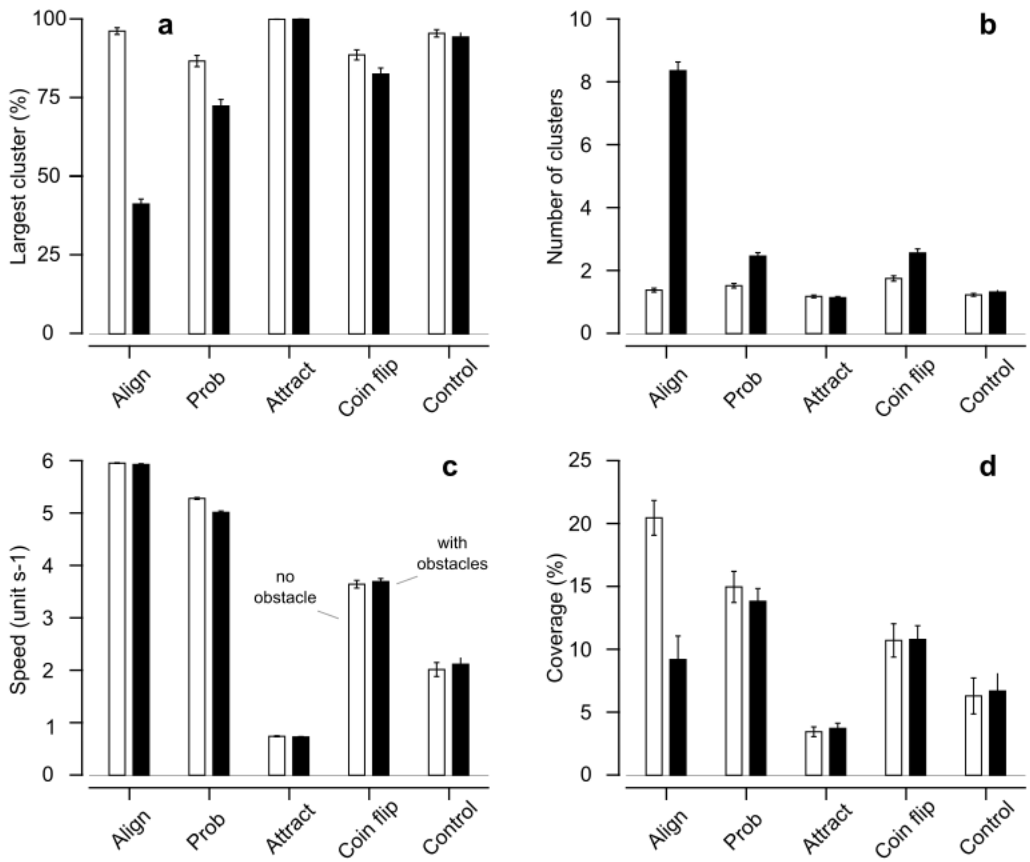

Figure 13: Comparison of variants when N = G-1. Figure shows results in obstacle-free (empty bars) and obstacle-filled (black bars) environments; i) **Align** (M = 0, K = 4), ii) **Probability-based** (M = 10, K = 2), iii) **Attract** (M = 20, K = 4), and iv) **Coin flip** (K = 0). In addition, a model adopted from Couzin et al. [15] is shown as a **Control**. Performance values are averaged over 100 trials and error bars indicate standard error of the mean. In all simulations, N = G-1, G = 200, s = 6 units s^{-1}. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

behaviours, and Coin-Flip randomly selects one. We did not expect to see such a significant difference caused by the difference in behaviour selection method. Although both Control and Coin flip are able to achieve higher levels of cohesion than the Probability-based variant they can not compete with it's mobility performance.

4.1.2 Six neighbours, (N=6) (Experiment 1)

The results show it is not essential for individuals to be informed on all members of the group to achieve optimal performance. When we reduce N from G-1 to 6 [fig.14] we see a drop in cohesion for Probability-based, Coin flip and Control variants but overall performance is not significantly reduced. The Probability-based variant retains the highest performance in obstacle-filled environments and second highest in obstacle-free environments. For both the Align and Attract variants we see little difference in performance; the results mainly mirror the trends shown by unlimited neighbour results. In both variants that focus on only one behaviour we see little change in performance; this implies that N is more significant for variants that switch between alignment and attraction behaviours. The biggest change observed is the speed increase seen in Control. This increase means that now the difference between Coin-flip and Controls performance is statistically insignificant.

4.1.3 Behaviour distribution for variants (Experiment 1)

The results show that mobility and cohesion performance is not dictated by the volume of behaviour selected (i.e., the Probability-based variant is able to achieve 80% of the Align variants speed with 50% of alignment behaviour selection). When we visualise the behaviour selection distribution of the five variants, [fig. 15] displays the underlying differences in decision-making and how that reflects in the performance. We observe that the as variant's use higher percentages of attraction behaviour the percentage of avoidance increases. In contrast high alignment ratios do not cause the same dependency. The Probability-based variant shows that it is possible to maintain a high level of cohesion and a fast speed by balancing favourable ratios of behaviour selection. The Control variant does not show a breakdown for behaviour selection, because its method of selection is the average of the two behaviours. We can however observe its avoidance rate; it shows that this method of selection requires higher levels of avoidance behaviour than the

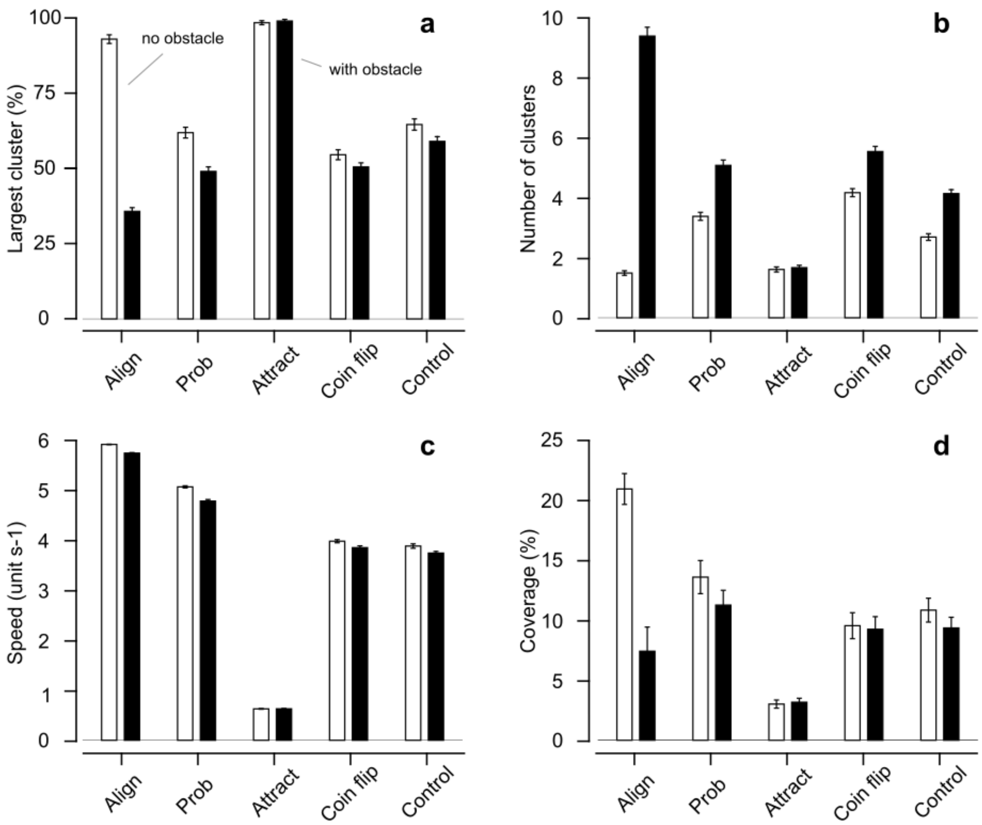

Figure 14: Comparison of variants when N = 6. Figure shows results in obstacle-free (empty bars) and obstacle-filled (black bars) environments; i) **Align** (M = 0, K = 4), ii) **Probability-based** (M = 10, K = 2), iii) **Attract** (M = 20, K = 4), and iv) **Coin flip** (K = 0). In addition, a model adopted from Couzin et al. [15] is shown as a **Control**. Performance values are averaged over 100 trials and error bars indicate standard error of the mean. In all simulations, G = 200, and s = 6 units s^{-1}. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

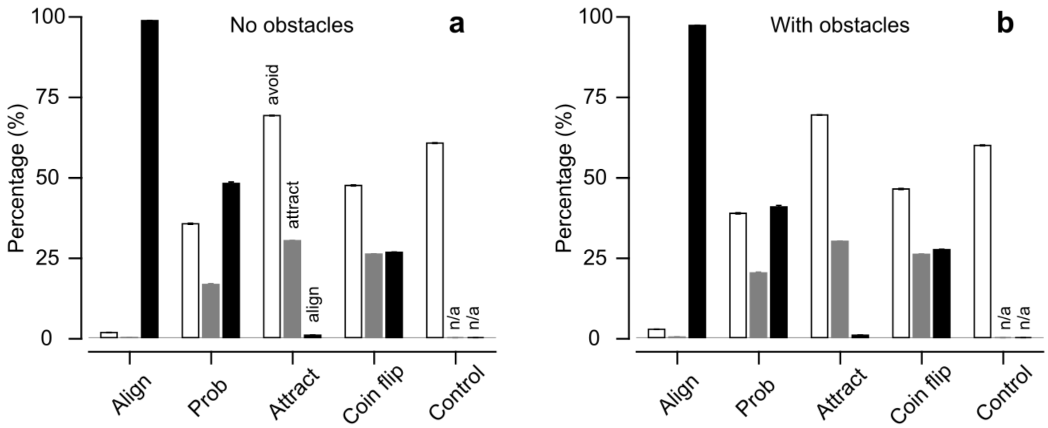

Figure 15: Comparison of behaviour distribution in variants; i) **Align** (M = 0, K = 4), ii) **Probability-based** (M = 10, K = 2), iii) **Attract** (M = 20, K = 4), and iv) **Coin flip** (K = 0). In addition, a model adopted from Couzin et al. [15] is shown as a **Control**. Tested in obstacle-free (a) and obstacle-filled (b) environments. Performance values are averaged over 100 trials. In all simulations, G = 200, s = 6 units s^{-1} and N = 6. Percentage relates to the total percentage a behaviour contributes against all decisions made by whole group over all trials.

random selection of a behaviour used in the Coin flip variant.

4.1.4 Variant collision rates

Across all variants the collision rate is extremely low; approximately 1 in every 19,000 movement selections leads to a collision. There is a noticeable difference in the rates of collisions for different variants, shown in [table.6]. We observe a trend for collisions to increase slightly when obstacles are added to the environment, which was expected as the difficulty of traversal is increased. The results show an improvement in the collision rate for Coin flip, Control and Attract variants when N is reduced, this implies that, for these variants, data from agents with a closer proximity is more valuable for reducing situations with collision risk. In contrast, we notice little change or a slight increase in collision rates for Align and Probability variants under the same conditions. It is possible that these variants need a higher number of neighbours in obstacle-filled environments for optimal performance.

Table 6: **Collision rates for compared variants**

variant	N = g-1		N = 6	
	obstacle free	obstacle filled	obstacle free	obstacle filled
Align	5.6	7.6	4.3	8.9
Coin flip	28	30.11	15.6	17.3
Prob	15.2	16.5	15.8	18.4
Control	36.1	52.3	24.4	23.7
Attract	259.3	259	199.8	200.5

4.2 How N influences performance between variants (Experiment 2)

Our findings show that 6 neighbours are the optimal number for creating cohesive and mobile groups with the Align variant in obstacle-free environments. This mirrors the findings of Ballerini et al.[10]. We observe in [Fig.16] that the performance makes a steep increase between N = 1 to N = 6. After this steep increase there is then a clear plateau in performance. This optimal N value is not duplicated in obstacle-filled environments; the performance is much lower and there is no clear plateau once N = 6. Obstacle disruption to the group without a method of attraction causes a large cohesion issue for the Align variant, and it sees a large increase in splits and a reduction of the largest cluster size.

In the Probability-based variant we observe a much slower, consistent increase in performance up until N = 6, and then a more gradual increase until N = 9, before we start to encounter a plateau in performance. [Fig.14e,f and h] shows that the Probability-based variant has a higher starting performance at very low levels of N compared to the Align variant. [Fig.14c and g] show that the addition of obstacles makes little difference to the largest clusters speed of either variant, implying that obstacles challenge cohesion, for these variants, more than they challenge mobility. Although N = 6 is not the optimal value for this variant it does account for the majority of its performance.

4.3 How M influences performance (Experiment 3)

In obstacle-filled environments the optimal range spans from M = 8 to M = 12. In this range we observe a trade-off emerge, as M increases so the largest

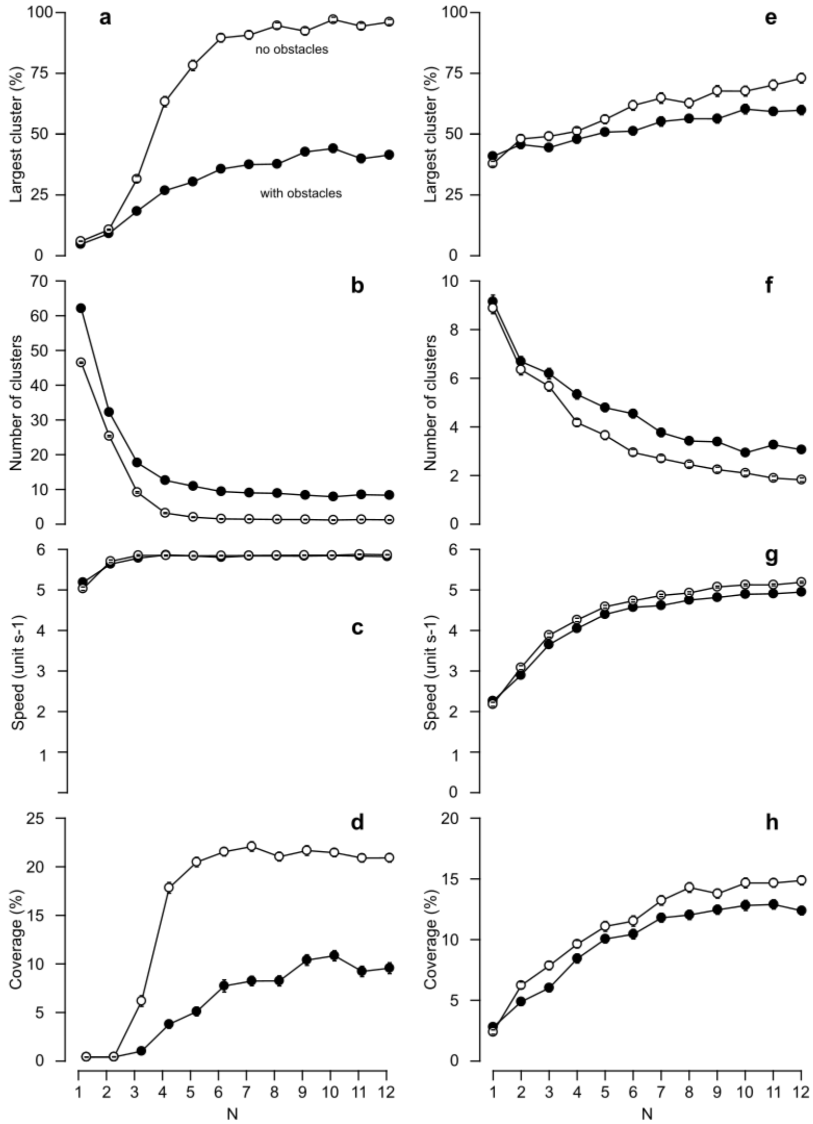

Figure 16: Comparison of variants, Align (left column) and Probability-based (right column) with N value range 1-12, in obstacle-free (empty points) and obstacle-filled (black points) environments; **Align** (M = 0, K = 4), ii) **Probability-based** (M = 10, K = 2). Performance values are averaged over 100 trials. In all simulations, G = 200, s = 6 units s^{-1}. **a&e**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b&f**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance) **c&g**) Speed of the largest cluster. **d&e**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

cluster size increases, but the speed reduces. So as M increases groups become more cohesive but slower. We can see that in an obstacle-free environment any increase in M leads to a decrease in performance; M = 0 (Align variant) is the highest performing. We observe in [fig.17] that once M > 15 the performance converges for the two environments and it flattens. Above M = 15 the mobility is reduced to a point where obstacles no longer noticeably impact performance.

4.3.1 Behaviour distribution as a function of M (Experiment 3)

When we view M as a function of behaviour selection, we can identify that our highest performing section (M = 8 to M = 12) is the area that sees behaviours converge to their most even mix. We observe that the ratio of attract plateaus at M = 13; any increase in M beyond that point causes a reduction in alignment, and an increase in avoidance. Using our behaviour selection model this sets a cap of the selection the attraction behaviour to no more than 28% of the time. In [fig.18] we can see that the level of alignment selection drops sharply from M = 7 to M = 12, indicating that this is range in which individuals start to struggle to maintain this number of neighbours in the z_{align}. This figure shows that obstacles have a minimal impact on the trend of behaviour selection, as a function of M. We observe a slightly higher ratio of avoidance behaviour, towards mid M values, at the cost of less attraction and alignment behaviour.

4.3.2 Polarisation and angular momentum as a function of M (Experiment 3)

We can see from [fig.19a] that as M increases, polarisation drops. This is caused by the decrease in alignment behaviour, and mirrors the trend seen in [fig.18] and [fig.17c]. The alignment behaviour allows groups to stay polarised, reducing the probability of avoidance, and subsequently reduces disorder in the group, thus maximising speed.

[Fig.19b] shows that groups display higher angular momentum in obstacle-filled environments at lower values of M. We see that once M > 10 that obstacles stop having an influence on angular momentum and the values converge, this may occur because as M increases the group becomes less mobile and is less likely to encounter as many obstacles.

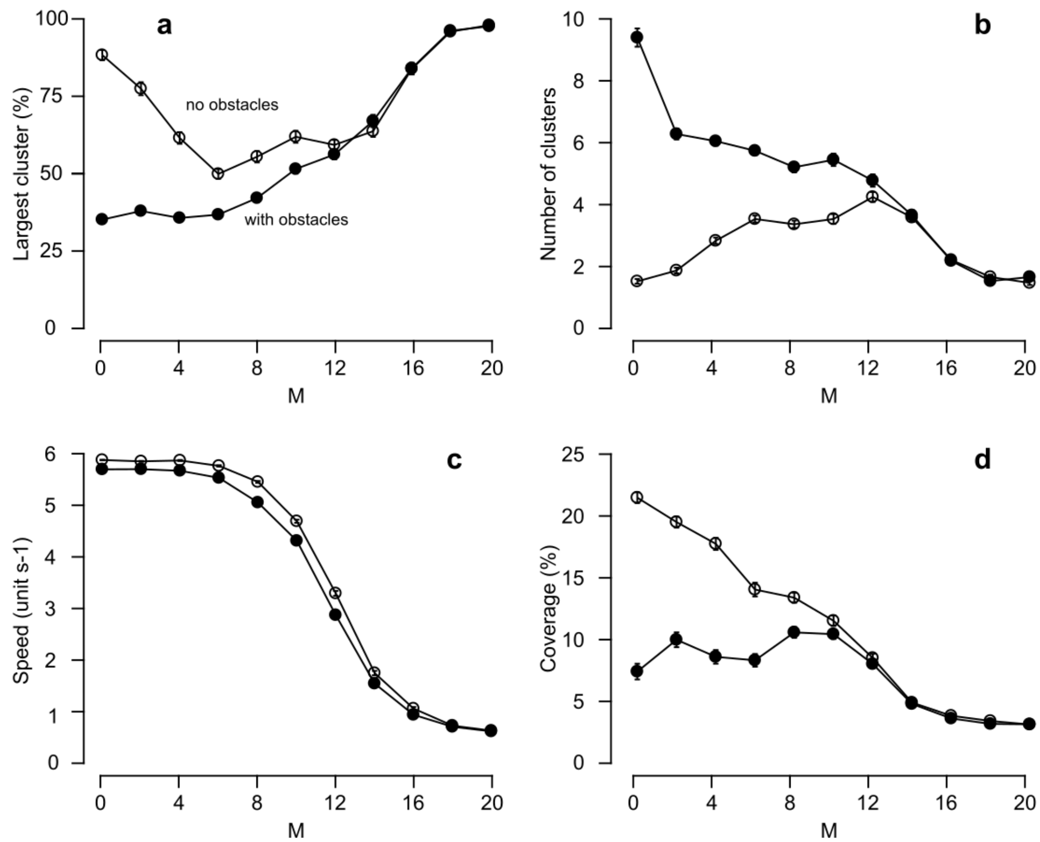

Figure 17: Visualisation of how change in M value influences performance in obstacle-free (empty points) and obstacle-filled (black points) environments. Performance values are averaged over 100 trials. In all simulations, G = 200, s = 6 units s^{-1}, N = 6 and K = 2. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

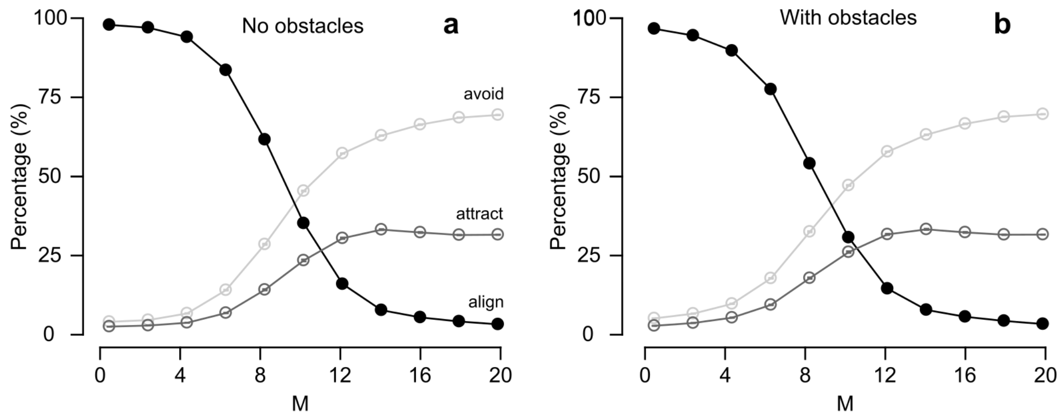

Figure 18: Visualisation of how behaviour selection changes as a function of M. Performance shown in obstacle-free (left) and obstacle-filled (right) environments. Performance values are averaged over 100 trials. In all simulations, G = 200, s = 6 units s^{-1}, N = 6 and K = 2. Percentage indicates the ratio of the total number of behavioural selections made by the entire group.

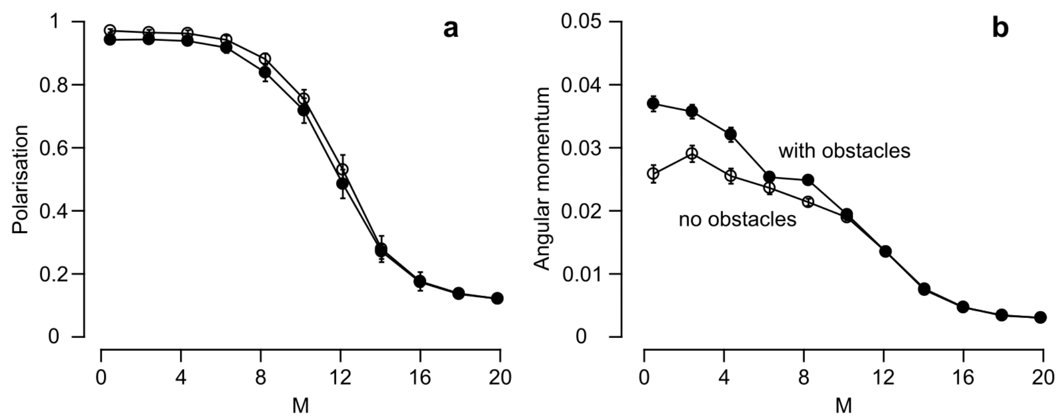

Figure 19: Visualisation of polarisation and angular momentum as a function of M. Performance shown in obstacle-free (open dot) and obstacle-filled (closed dot) environments. Performance values are averaged over 100 trials. In all simulations, G = 200, s = 6 units s^{-1}, N = 6 and K = 2. Polarisation measures how aligned the largest group is 0 being fully unaligned and 1 being fully aligned across the duration of the trials. Angular momentum indicates how synchronised the largest groups turning angle is, relative to the groups centre of gravity, across the duration of all trials.

4.4 How K influences performance (Experiment 3)

[Fig.20] shows there is no discernible trend observed in the performance of the Probability-based variant, when we change the K value (excluding K=0, as under this condition the variant becomes the Coin flip variant). Although we know that changing K influences the flexibility of behaviour selection based on n_{align} it does not create enough of a measurable trend change in our performance metrics.

4.5 How the performance of uninformed variants compares to informed variants (Experiment 4)

Uninformed coverage performance peaks at 8.5% in the p_{align} range of 0.5 - 0.7. However, informed decision making (Probability-based variant) outperforms the uninformed pre-set behaviour ratios on coverage at every ratio. The p_{align} ratios are an expansion of the 0.5 p_{align} ratio of the Coin flip variant to include a wider range of p_{align} probabilities. [Fig.21d] shows that the coverage performance for the full range of pre-set P_{align} values is, at minimum, 20% lower than the Probability-based variant(dashed-line). This shows that the timing to decisions is an important feature to the Probabilty-based variant's success. In [fig.21a,b and c] we can see ratios where the uninformed variants can outperform the informed in mobility and cohesion. However, when those specific ratios perform highly on cohesion they perform very poorly on mobility, and vice-versa.

4.6 The influence of speed (Experiment 5)

We find that the range of M = 8 to M = 12 generates the best performance. It reveals an optimal speed for our model at 9 units s^{-1} (black line). The general trend is, that as the speed increases cohesion becomes more difficult, but twice as fast does not translate to half as cohesive. Groups with slower speeds maintain a higher cohesion and a higher relative max speed. This results in a more consistent coverage performance across a larger range of M vales. However, the M range of 8-12 allows groups with faster speeds to take advantage of a 'sweet-spot' where the higher absolute speed and the relative high level of coverage, combine to generate high coverage results.

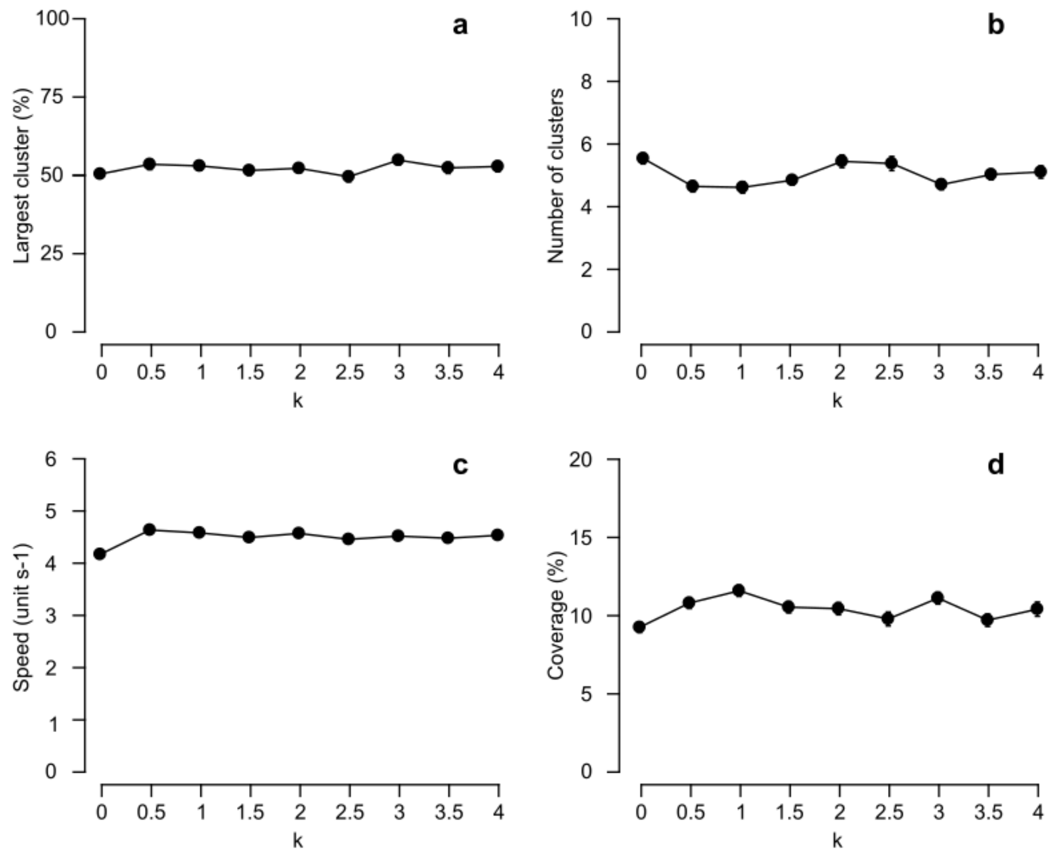

Figure 20: Visualisation of how the probability-based variant's performance changes as a function of K in obstacle filled environments. Performance values are averaged over 100 trials. In all simulations, G = 200, s = 6 units s^{-1} and N = 6. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

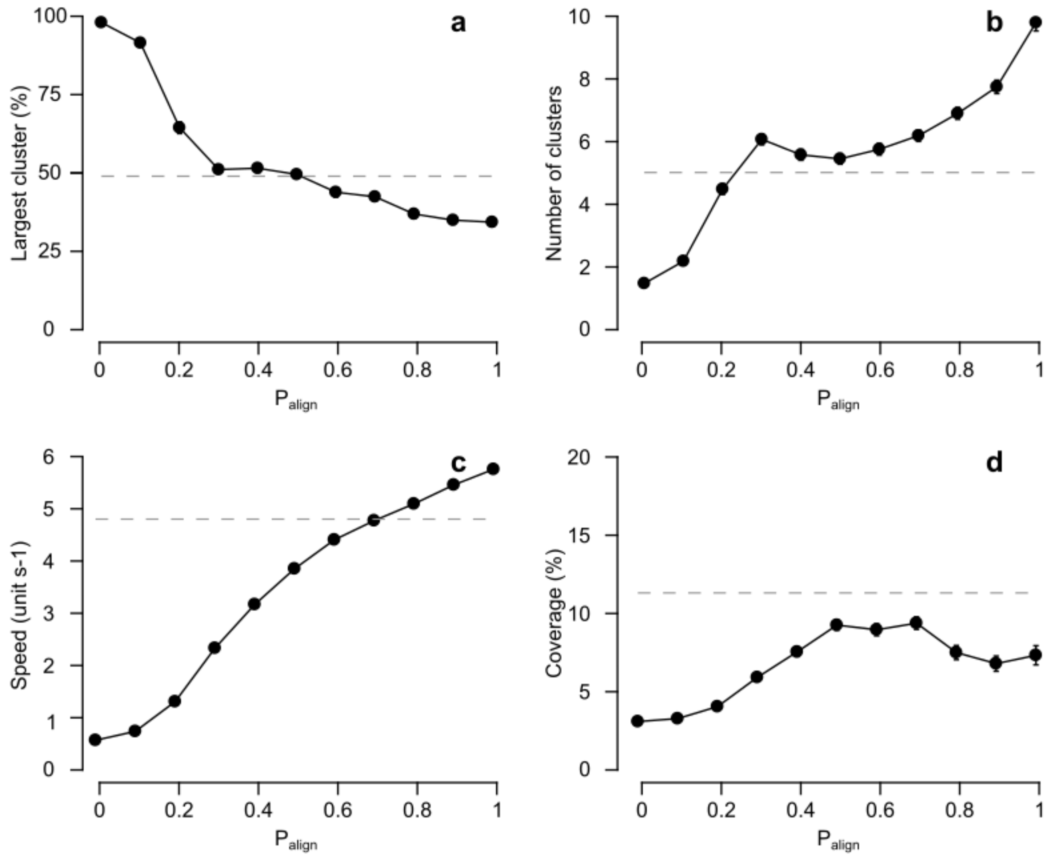

Figure 21: Comparison of uninformed pre-set P_{align} ratios (black points) and highest performing informed decisions from the Probability-based variant(dashed line). Performance values are averaged over 100 trials. In all simulations G = 200, s = 6 units s^{-1} and N = 6. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

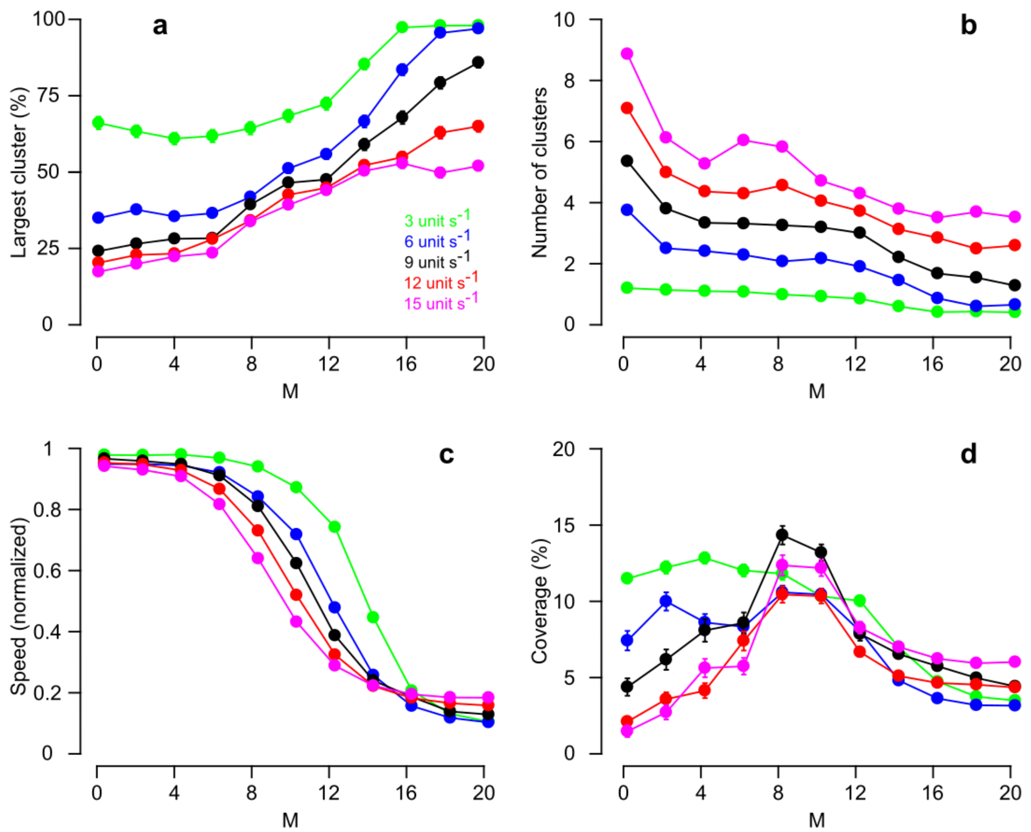

Figure 22: Visualisation of how change in M value influences performance at different speeds (3,6,9,12,15 units s^{-1}) Performance values are averaged over 100 trials. In all simulations G = 200 in an obstacle-filled environment. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

4.7 The influence of group size (Experiment 6)

Our results show that as group-size increases maintaining cohesion is more difficult, but the largest cluster size is not limited, and as such, splits are not solely influenced by the number of individuals in a group. We can observe from [fig.23a and b] that for all variants, the number of clusters and the size of the largest cluster show, that splits are not symmetrical (i.e., if at group size 200, the Probability-based variant, has a largest cluster that is 50%, and a total of 4 clusters, the other 3 clusters cannot be symmetrical with the largest). We see an anomaly for coin-flip, as it shows a very high velocity for group size 50 which is unexpected. This is due to the small group size and low cohesion performance. Agents in small clusters are able to fit all members of the group into their $\mathrm{z_{align}}$, as such, without any neighbours to attract to, the Coin Flip variant cannot make any other choice than to run the alignment behaviour, this means it takes on the properties of the Align variant.

4.8 The influence of obstacle density (Experiment 7)

The Probability-based variant shows a resistance to splits in higher obstacle density environments. We can see in [fig.24b] that both other variants overtake the Probability-based variant in number of clusters. All other measures hold very similar trends and performance. We see a performance drop in coverage that is not explained by a corresponding drop in cohesion or mobility; we lack conclusive proof, but from watching visualisations, we believe that as the density increases it can create a 'trap' for swarms, where they traverse to a location that is surrounded by obstacles. This 'trap' causes them to be redirected around in the same voxel space and as such limits exploration. As we recognise only novel exploration for our coverage measure this would cause a noticeable decrease in coverage.

4.9 The influence of Zalign size (Experiment 8)

The results indicate that there may be an optimum ratio for $\mathrm{z_{align}}$ and $\mathrm{z_{attract}}$ as increasing the $\mathrm{z_{align}}$ size beyond 14 units showed a decline in coverage. [Fig.25d] shows that increasing our rAlign increases cohesion and maintains higher speeds through a wider range of M values. This translates into significantly higher coverage across all values of M for both larger sizes tested.

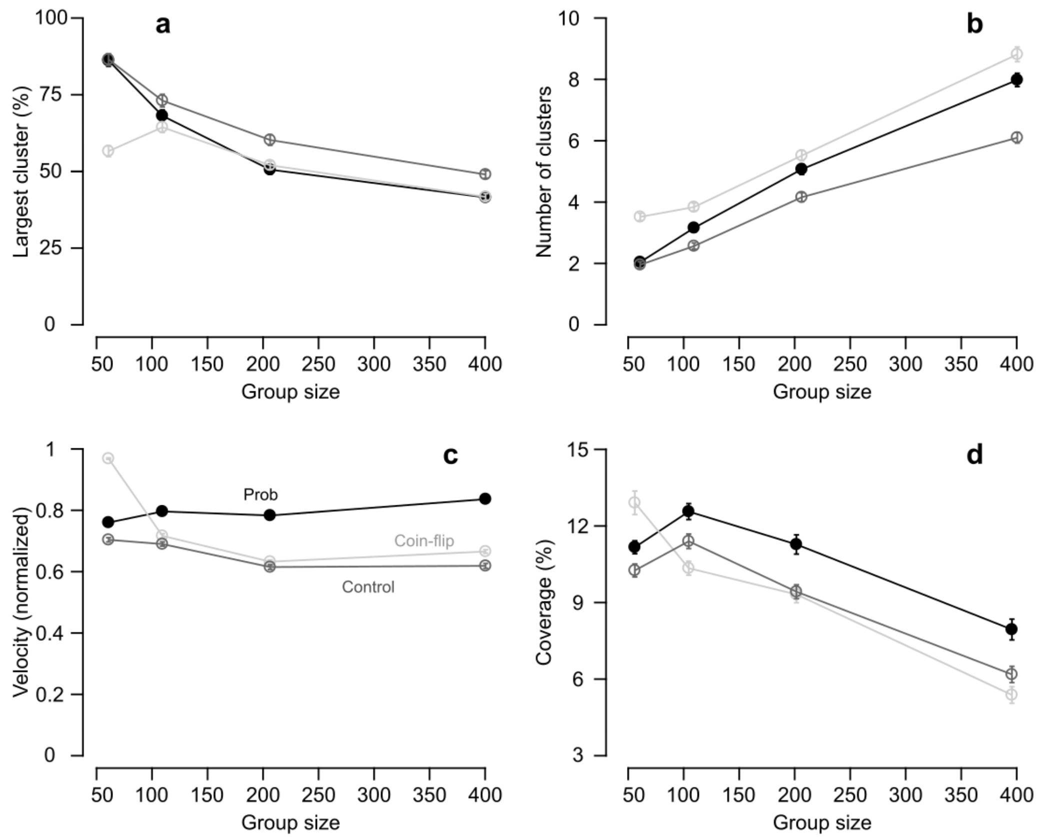

Figure 23: Visualisation of how change in group size influences performance for three variants; i) **Probability-based** (M = 10, K = 2), ii) **Coin-flip** (K = 0), iii) **Control**. Performance values are averaged over 100 trials. In all simulations G = 200 in an obstacle-filled environment. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

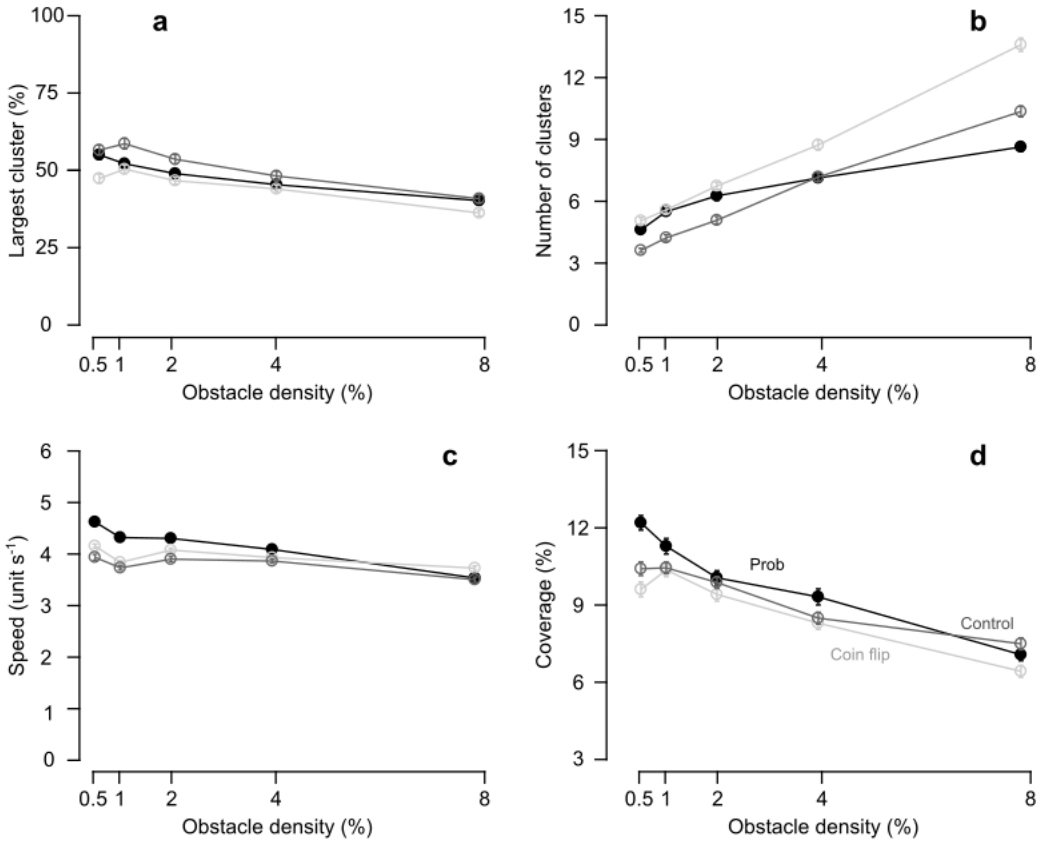

Figure 24: Visualisation of how change in obstacle density influences performance for three variants; i) **Probability-based** (M = 10, K = 2), ii) **Coin-flip** (K = 0), iii) **Control**. Performance values are averaged over 100 trials. In all simulations G = 200 with obstacles present at densities 0.5%, 1%, 2%, 4% and 8%. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

However, the smaller of the two outperforms the larger consistently, until high values of M, where the speed starts to drop. Cohesion and speed are similar in performance for both, but 14 outperforms 18 in coverage. We believe that as a zone size shrinks this negatively influences the ability of the behaviour to run optimally which is why we see this drop in performance as the ratio changes.

4.10 The influence of heterogeneity (Experiment 9)

Generating heterogeneous groups by combining two set of agents using differing variants failed to create any measurable improvement. In all items of [fig.26] we can observe that for every performance metric, and every percentage ratio split of the two variants, we were unable to find a performance that surpasses their equivalent homogeneous group (in this figure 0% represents the Align variant and 100% represents the Probability based variant). Obstacles have a negative influence in a manner consistent with how they influence homogeneous groups; creating heterogeneous groups in this way has no measurable influence on obstacles. We hypothesised a synthesis of these variants could outperform the individual variants but it is clear that for this method it is not the case.

Generating heterogeneous groups by having agents switch between differing variants shows potential to create an improvement over homogeneous groups, but only in obstacle-filled environments. In obstacle-filled environments a 50% split between the variants results in an increased largest cluster size compared to the homogeneous groups. We observe a lower number of clusters between the range of a 50-80% split. Any percentage inclusion of align sees an increase in speed when compared to a homogeneous probability variant. In terms of coverage, we see a very slight increase at 50% and 80%, compared to the performance of the Probability-based variant. The performance in obstacle-free environments the highest performer defaults back to 0% Probability-based variants (the Alignment variant) that we have seen in Experiment 1.

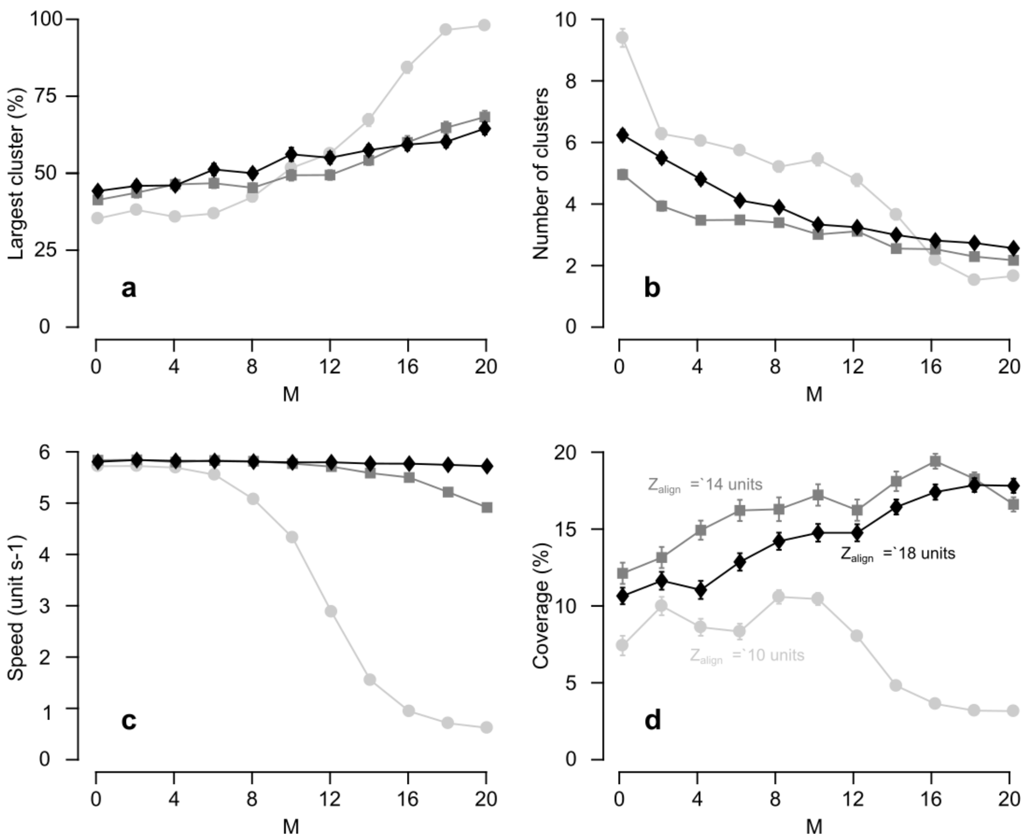

Figure 25: Visualisation of how change in z_{align} volume influences the performance of M. Variant types combined; **Align** (M = 0, K = 4), ii) **Probability-based** (M = 10, K = 2). Performance values are averaged over 100 trials. In all simulations G = 200, in obstacle-filled environments. **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

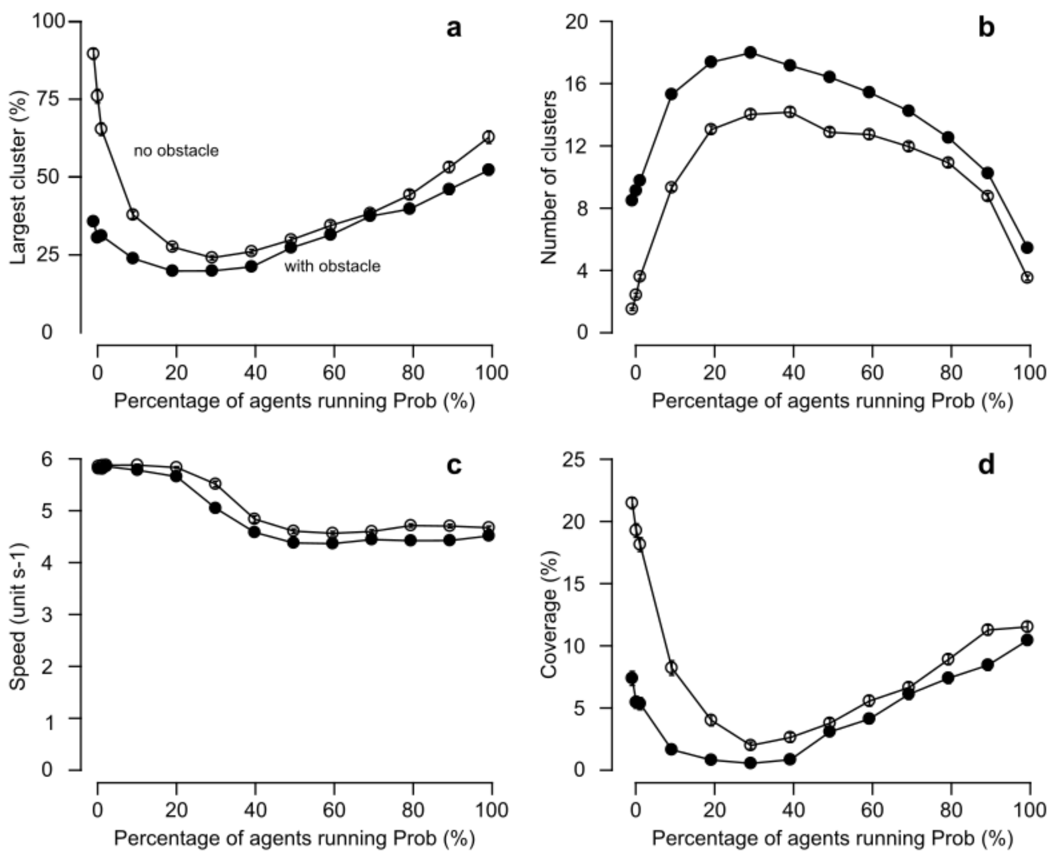

Figure 26: Visualisation of how generating heterogeneous groups from multiple variant types influences performance. Variant types combined; **Align** (M = 0, K = 4), ii) **Probability-based** (M = 10, K = 2). Performance values are averaged over 100 trials. In all simulations G = 200, in obstacle-filled environments (closed dots) and obstacle-free environments (open dots). **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

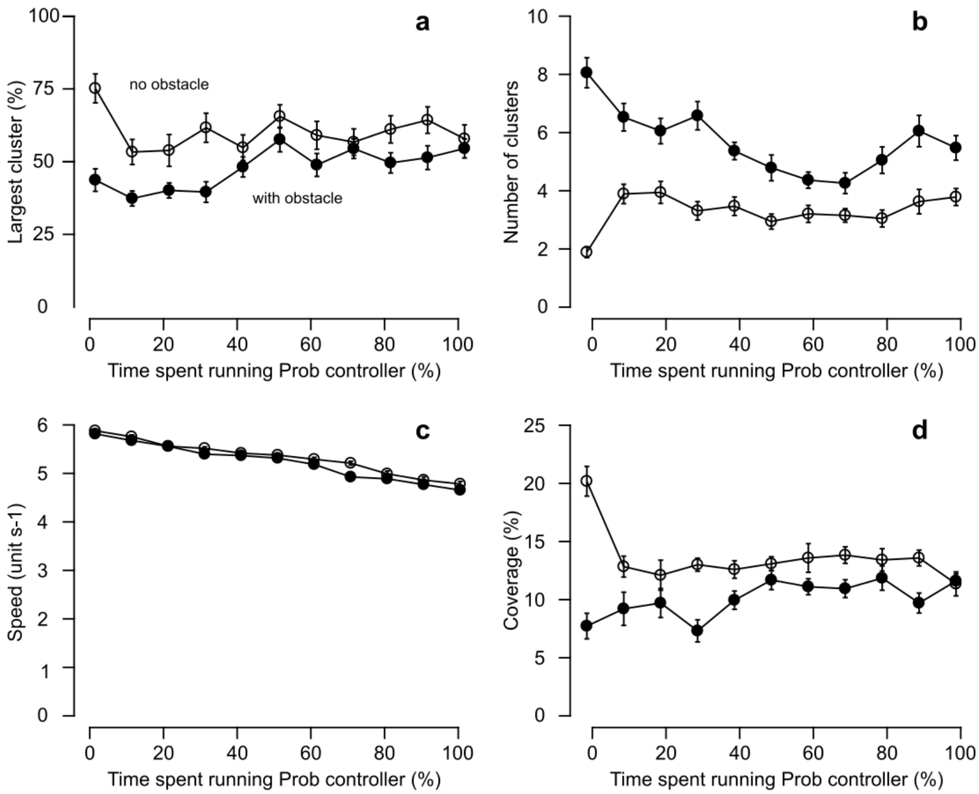

Figure 27: Visualisation of how generating heterogeneous groups from individuals propensity to select a variant influences performance. Variant types combined; **Align** (M = 0, K = 4), ii) **Probability-based** (M = 10, K = 2). Performance values are averaged over 100 trials. In all simulations G = 200, in obstacle-filled environments (closed dots) and obstacle-free environments (open dots). **a**) Number of agents in the largest cluster is shown as a percentage of the total group size. **b**) Number of clusters which is indicative of the coherence of the group(i.e. a high number of clusters suggests a poor coherence performance). **c**) Speed of the largest cluster. **d**) Coverage at 30% group size threshold (number of voxels entered by at least 30% of the group size).

5 Discussion

5.1 Summary

We proposed a novel behaviour selection model based on simple sensory feedback. Our model allows individuals to use the number of close-range neighbours to determine behaviour selection. We believe that the simplistic mechanism of counting neighbours would easily translate into robotic platforms and has biological plausibility. From the controller we were able to make different variants by modifying M. The Align variant (M=0) performs best in obstacle-free environments, it is highly mobile, and has a low level of avoidance behaviour. The disadvantage of the Align variant is that it is not suitable for obstacle-filled environments; we find that alignment behaviour heavy variants cannot maintain cohesion when presented with the challenge of avoiding obstacles. The Attract variant (M=20) is highly cohesive but very immobile, it selects the avoidance behaviour for approximately 75% of its decisions, and as such, is unable to move the group. In terms of coverage, our probability based variant (M = 10) performed best in obstacle-filled and second best in obstacle-free environments. It has a low collision rate, and was robust when speed, group size, and obstacle density increased.

5.2 Main findings

A major aim for this project was to try to ensure that our simulation environment and model were designed, wherever possible, with biological plausibility and computational efficiency. We decided to use a three-dimensional simulation to ensure our results would be more relevant to real-world environments. We implemented simplistic methods to see if it is possible to achieve a high level of performance, while requiring less exertion on individuals. We designed our model to allow agents to select only a single behaviour at a given time-step, rather than averaging multiple priorities. We focused on reducing the number of neighbours required for calculations. We designed behaviours to be simplistic in execution (e.g., move in the opposite direction from an obstacle). Our fov has no priority for neighbours in different areas and is a simple circular shape. With our fov we also consider external influences: how swarms can function in low-visibility environments or with short-range sensing ability. We know robotic platforms may have to rely on vision systems that are only effective to a certain range and underwater environments have poor long-range visibility. Both scenarios would require collective motion methods that work with limited range sensing. Our model's r_{fov} (12 body lengths) is smaller than similar models from the literature (Viscodo et al.: 180BL [23], Kunz & Hemelrijk: 25-50BL [21], Couzins et al.: 15-30BL [12]). Our individual's r_{align} is designed to simulate short range orientation identification. We believe it seems a more plausible premise that identification of neighbours' orientation is easier at short-range compared to long-range.

5.2.1 Timely informed decisions are key to performance

From the comparison of the variants, specifically their behaviour ratios, we observe that the alignment behaviour and attraction behaviour maximises mobility and cohesion respectively. Therefore, we believe the Probability-based variant's performance stems from being able to select the most appropriate behaviour for its situation more often than the other variants. This is supported by the fact that when we statistically match the P_{align} to $P_{attract}$ ratio, to that of the Probability-based variant, but continue to make random decisions based on the ratio rather than taking into account n_{align} the performance does not match that of the probability-based variant. This indicates that the timing of decisions is key and that taking into account the number of neighbours around you is an effective method of identifying the timing.

5.2.2 Conflicting priorities can be better managed with informed priority rather than compromise

We observed that several of our variants can outperform the Control variant that uses an averaging technique to decide optimum heading direction. Firstly, comparing the performance of the Coin-flip and Control variants (for $N = 6$) the results show that the coverage performance is statistically interchangeable (cohesion was slightly better with the Control variant and speed was slightly higher on coin-flip). In these results we consider two things, firstly, the Control variant considers double the number of agents at every time-step (12 compared to 6, as the Control variant uses n_{align} and $n_{attract}$ for heading direction calculations). Secondly, the Control variant requires considerably more avoidance than the Coin-flip variant. Based on our belief that correct behaviour selection improves performance, we can see that selecting randomly between the two behaviours, or combining, causes similar coverage results. We believe this is because the averaging of two behaviours causes more occasions of redundant behaviour selection (e.g., more unneeded alignment behaviour, leading to higher avoidance). We believe randomly selecting a behaviour causes optimum selections to be missed (e.g, attract to be selected when align would have been the optimal choice). When comparing the Probability-based variant, which makes informed single behaviour decisions, we see that it outperforms the Control variant on coverage in all variations of environments and values of N. We don't believe that our results conclusively determine that single decision-making can always outperform averaging, but we do determine that it is possible to accomplish better performance with single decision controllers, and we believe that optimum behaviour selection is key.

5.2.3 The ratio of an individual's fov is important in challenging environments

A problem we began to explore with our model was how swarms can function under challenging conditions (e.g., low visibility, limited hardware). Based on our results, our low-range r_{fov} proves it to be a feasible option for collective motion under these conditions. Something key to these findings, when we adapt the size of r_{align}(which changes the volume ratio of z_{align} and $z_{attract}$) it has a clear impact on performance. We see an increase of 2BL in r_{align} results in an increase in coverage across all values of M. However, extending r_{align} a further 2BL results in a drop in performance. This indicates that the ratio between the two zones is important for making sure both behaviours contribute to the overall heading direction across time. These changes were made without extending r_{fov}. The literature holds examples of more complicated fov implementations; A-symmetrical alignment zones[48], and non-interaction zones[22]. When we consider these modifications along with the multiple ratios available with r_{fov}, r_{avoid}, and r_{align} the search space becomes very large, and would require further testing to explore the entire parameter space. We suspect that there is no universal framework for fovs, it seems more likely that the sensing ability and movement of the individuals involved dictates to some degree the most effective fov set-up for optimum collective motion.

5.2.4 Avoiding obstacles is not a straight-forward problem for groups running simplistic models

We used obstacle density as a way to test our controllers performance under difficult environmental conditions. The results show that the Probability-based model has the best coverage results, under these conditions. Obstacles show a consistent impact upon all variants that move enough to encounter them. We can see from the results that obstacles create more disruption to cohesion that they do to group speed. This implies that obstacles do not significantly halt movement but disrupt the group's structure. Therefore, variants that maintain a robust group structure will be more resilient to the effects of obstacles. It seems likely that biological agents have a distinct system for navigating their environment, and unlike our model, do not rely on the emergent properties of their collective motion rules to deal with obstacles. Different priorities are probably given to large impassable sections of environment compared to the priorities of neighbours. However, in very low-visibility conditions pre-planning of routes to avoid obstacles may not always be possible, and as such, this method is valuable in those scenarios.

5.2.5 The probabilistic approach achieved through M,K and N improves performance but there is still room for further progress

Across most experiments we treated M as a range. Even though we noticed different behaviour distributions across all values of M, the distinct variants are represented at low (Align), mid-range (Probability-based) and high (Attract) values of M. The M range we explored is not an independent range, it is tied to an individual's r_{align}. The range we explored (M0 - M20) is relative to the number of neighbours that can comfortably fit into the z_{align}. We observed that as r_{align} changes, the range m=0 to m=20 no longer applies in the same way; M=20 would no longer be considered an attraction only variant if the z_{align} is much larger. Care would need to be taken when defining the range for differing r_{align} values to ensure the model had an accurate response to n_{align}. We found no single N value that could be applied to satisfy all ranges of M. The number of neighbours an individual considers is an often discussed topic in the literature. We found that our Align variant follows a similar rule set to the Ballerini et al. model [10]. Their model uses topological alignment to achieve collective motion under the threat of predation. Although our implementation relies on a low-range metric model, we both find that six neighbours maximises performance. This implies that an alignment-based model requires only 6 neighbours, irrespective of whether it uses topological or metric identification of those neighbours. The Probability-based optimum for N was nine, but we observed from the literature swarm examples that were able to achieve lower numbers of neighbours with stricter fov[16]. Often models that can use lower numbers of neighbours implemented more complicated fov frameworks, such as A-symmetric avoidance zones [16], directionally focused fovs[20], or more complex shapes [23]. This would suggest that prioritising in sensing abilities, through dedicated zones or specific shapes, could be key to reducing the number of neighbours needed to calculate accurately. We believed K would be important in generating noise in the decision-making process. Existing research had shown that noise was necessary for swarms, and could improve performance[52]. However, in our simulations we saw very little difference in performance across the full range of K (excluding K=0 where it becomes the Coin-flip variant). We believe that the frequency of decisions per second removes any significant impact K could could have, as it has an averaging effect, which results in very similar behavioural selection. With hindsight, we may have been more successful by using a fuzzy logic approach to determine behaviour-selection, rather than the logistic function. Fuzzy logic can be effective for problems with imprecise membership (M range if considered low, medium, high) and can deal well with decision making based on cognition of noisy data [53]. It also complements a biological understanding or a vision implemented solution, where counting a precise number of neighbours is less plausible than reacting to the concept of none, some or many neighbours around you.

5.2.6 Our model can be easily expanded to create more optimal solutions

The model is universal in the sense that Align, Attract, Probability-based and Coin flip variants can all be generated by modifying M and K values. This flexibility opens up new possibilities to develop more adaptive control architectures, as M and K could be modified depending on external stimuli. Research shows support for this kind of state transition in biology [54]. This would allow the distinct strengths of multiple variants to be available in a combined variant (e.g., a switch from the Align variant to the Probability-based variant if obstacles are detected). We began to observe success for this kind of model without an intelligent mechanism for switching variants in our heterogeneous experimentation results.

5.2.7 Relevance of our results to biological insights and robotic implementation

Our model showed that dealing with conflicting priorities in collective motion can be solved effectively by choosing a single option. While it is less complex than averaging conflicting priorities this does not prove that biological agents use this method. However, it does offer support to this as a plausible option. The timing of decisions proved to be key for performance, and our method of decision making relied upon counting neighbours. In nature animals can recognise other animals from within their species. Therefore, counting the number of individuals in close proximity would not be a massive leap. We do believe that the process of counting should be modelled in a non discrete way (e.g., fuzzy logic), we discuss this in more detail in the further work section.

In the literature, biological agents can be identified with personalities, often contrasting shy and bold agents [55]. Through the lens of our model we could interpreted our align agents as bold (due to their high speed and explorative nature) and attract as shy agents (due to their proximity to neighbours and minimal movement). With this in mind, our heterogeneity experiments imply that mixing bold and shy behaviours is not conducive to successful groups, but the fact that individuals may switch between shyness and boldness is much more successful. We would expect biological agents' shyness or boldness to be a spectrum and to be controlled externally via influences such as predation or hunger and internally by experience. We could conclude that the trade off between effective exploration and swarm cohesion is controlled by the distribution and fluctuation of 'shyness' or 'boldness' each agent displays.

Our model shares many aspects with Arkin's definition of robotic motor schema [56]. Motor schema can be used to create reactive navigation in robots by taking in and processing sensory data to select behaviours. Arkin states that from all the possible sensory data we select only what is relevant (n_{align} in our case). Other similar approaches [57] [58] successfully use hierarchical schema to control navigation in robots. Based on these examples we believe our model could be converted into a motor schema for a multi-agent robotic platform. We believe we have created a simple and effective model and while behaviours, decision-making, sensing ranges and the methods of selection are relativity straightforward to implement our simulator relies on individuals being able to measure distance and angles between agents effectively. When implementing this into a robotic platform we are posed with a problem; measuring distances and angles reliably and accurately is not a straightforward task for an agent who is gathering data from the environment in a non-precise fashion (e.g vision, LiDar). Thus, our model provides only the concept for a simplified controller. Although it would require further work to implement this model the next step on the way is possible; if given the specification of a robots sensors the simulation could be easily modified to test the level of precision required when considering neighbour positioning and angle calculation. If the precision needed is very high it would prove the model is not fit for robotic implementation in its current form.

5.3 Assumptions and limitations of the work

5.3.1 Assumptions

- **Individuals can locate neighbours position and orientation** - We provide individuals with the ability to identify neighbours orientations (up to 5 body lengths away) and positions (up to 12 body lengths away). We justify this as a visual ability that individuals would be able to use to identify the distance and orientation of neighbours based on their proximity.

- **Field of view** We assumed that individuals have a concentric, multi-zoned field of view. With 270 degrees of freedom in all directions from the heading direction. We assumed that agents are able to identify, using distance, which neighbours fall into each zone.

- **Behaviour implementation** For avoidance behaviour, we assume that individuals have the capability to calculate a heading direction that maximises divergence from identified obstacles. For alignment, we assume agents have the capability to calculate a heading direction that will match their neighbours orientation. For attraction we assume individuals have the capability to calculate a heading direction that will intercept the centre of gravity of a group of neighbours.

5.3.2 Simulator limitations

- **Individuals body shape** - Research shows that body shape has an impact on swarming behaviour [23]. Our model required a physical representation so that we could model collisions. We selected a spherical form so that calculating collisions would be less intensive, and to avoid our model over-fitting to that a particular body. It seems likely that the specifications of an individuals body shape contributes to how individuals traverse; we are aware that a spherical body would not be considered typical in nature or robotics.

- **No occlusion** - In our simulation we did not implement the occlusion of agents when there is no line of sight from an individual to a neighbour. Occlusion is a relevant problem in swarms, and research has shown occlusion is an important factor in swarm decisions, detection capabilities and positioning within the group [59]. We did not implement this capability due to the additional calculations required, and with the lack of realistic body shape previously mentioned, we believed adding occlusion to an unrealistic body form would have provided less conclusive or relevant results about the effects of occlusion.

- **Fixed speed** - Our model relies on agents having an internal constant drive to move them forwards. However, swarms are made up from multiple agents, traversing at multiple speeds, accelerating and decelerating. Research shows that individuals' speed, especially acceleration, is significant in information transfer and cohesion [60]. Constant speed is a common simplification that we encountered throughout our background research.

- **Simplification of obstacles** - In our model obstacles are free floating spheres, we chose this to reduce collision calculations. These are unrealistic obstacles and as such may have less relevance to how swarms avoid as a group compared to more varying shapes and sizes (that nature typically offers).

- **Environmental conditions** - Our aim with having a low range fov compared to other models was to simulate the conditions that can be found in underwater environments that have low visibility. We have simplified the issue and reduced the sensing capabilities of our model.

This ignores issues such as the clarity of water, and how the visible light spectrum is affected underwater. We also do not implement fluid dynamics, buoyancy, gravity, momentum or other physics-based mechanics to our simulation. We believe that these factors most likely have an impact on how swarms traverse, but the time required to implement these mechanics falls outside of the scope of this project

- **Simulation uncertainty** - For all simulations we control the seed used to generate random values used (e.g., agent/obstacle placement during initialisation). This allows us to re-run specific trials whenever required. We did not conduct specific testing to ascertain if our system was generating noise that was creating uncertainty between identical trials (e.g., inconsistent rounding errors that compound overtime and lead to significant changes in agents positioning). However, we can state that the data we captured from the trials is identical across multiple replicated trials and that during testing when we encountered errors they were always present or repeated trials until they were debugged and fixed. This provides us with a level of confidence that if there is inherent noise in the system its influence is not significant enough to alter the data we are collecting.

5.3.3 Analytic limitations

One of the biggest considerations we undertook when creating performance metrics was how to measure successful groups for mobility and cohesion. Our coverage measure requires cohesion and explorative movement which are the two indicators we decided we valued most. Due to the way that we divide the space into voxels and how agents are allocated to voxels we have the potential to cause anomalies (e.g., agents movement may run along a boundary line splitting agents between multiple voxels and not registering either voxel as explored). We believe that although this is a possibility, all variants tested are subject to this possibility and we have conducted enough trials to reduce the significance if it does happen.

5.4 Future work

In the process of creating this thesis, much of our experimentation revealed new hypothesises and potential routes of experimentation. We intend to develop the following lines of research.

A central focus for this project has been the number of significant neighbours. We hypothesise that the values and methods we currently use are not the optimum. We suspect that appreciating multiple neighbours, making calculations based on multiple variables of each neighbour, and doing this multiple times a second is a challenging task, and we aim to simplify it. We intend to use our current model, but with two modifications. Firstly, adapting the fov so that we can control the priority given to neighbours based on heading direction. Secondly, we will implement a more refined avoidance mechanism, based on matching neighbour's alignment and speed. Our hypothesis is that by reducing the volume of avoidance behaviour with a preventative method, individuals will not need to recalculate positioning as often. We will then perform experiments where individuals select a single neighbour from a pool of neighbours, where the chance of selecting that neighbour is weighted by distance. We will test different values for the number of agents in a pool, and different weighting techniques for selection. Ideally, we aim to develop a system that requires individuals to consider only one neighbour at a time, at a low update rate, and from a small pool of neighbours, without compromising performance.

We developed a system that allowed individuals to identify the direction of an external stimulus. We wanted individuals to have the ability to sense the strength of a signal across multiple sensors, so they could adjust their behaviour based on its location. We were inspired by taxis behaviours observed in biological systems. To complement this, we also plan to implement a more refined movement system than the one used in our experimentation. Individuals will be given the ability to control their minimum and maximum travel speed and their rate of acceleration, based on external influences (e.g., neighbour movement, stimulus strength) or internal influences (behaviour selection, simulated hunger). This would allow agents to have much more dynamic speeds that would match the priority or utility of the need at hand (i.e., agents could slow when presented with avoidance, or increase speed when attracting). Originally, the inspiration for this was creating swarms consisting of Braitenberg vehicles[61]. We are no longer taking this direction, and intend to utilise the systems differently. From the literature we observe that when exploring swarm behaviour, research often provided a common goal (e.g., food source, shelter, environmental conditions). Revisiting our previously mentioned reservations around constant speed, we intend to explore how external stimuli, numbers of informed individuals, and acceleration

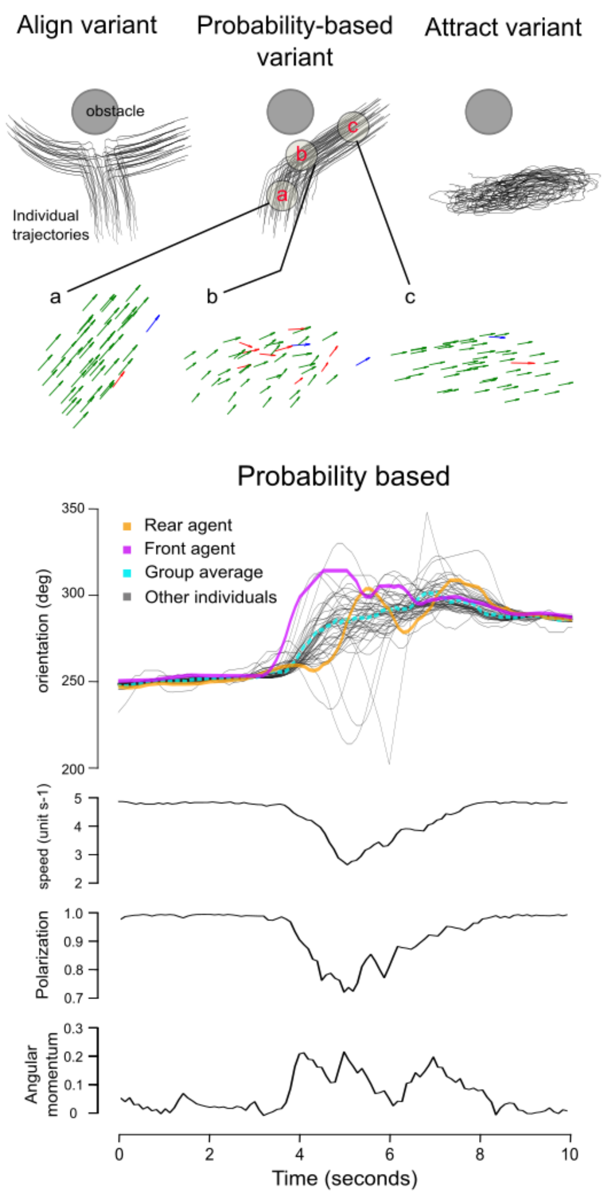

Figure 28: Preliminary results on (1) how different variants adapt to external stimuli (obstacles) and (2) how the Probability based variant reacts to an obstacle encounter. 2a) Change in orientation for all agents in group, including pink (first agent to encounter obstacle), orange (most rear agent in group), blue (average of the group). 2b) Groups average speed. 2c) Polarisation of the group. 2d) Angular momentum of the group

alignment influence collective motion. We plan to use our existing model, but replace constant speed with variable speed, acceleration and deceleration, and provide agents with the external signal sensing. We plan to test what ratios of informed individuals (given ability to sense) vs uninformed individuals influences collective motion most positively. Also, how individuals may use acceleration alignment as a method of information transfer to assist predation avoidance.

We made an initial simple attempt at exploring heterogeneity in our experimentation. In the process of building our model, we devised the capability to generate multiple distribution ranges on specific variables (e.g., normal distribution on turning rates, normal distribution on M values), and the ability to insert noise into our system at specific points (e.g., sensors, internal calculations, movement execution of movement). We intend to use these systems to explore heterogeneity further, but due to the size of the search space we plan to use a heuristic search method(e.g., evolutionary approaches) to explore the parameter space more effectively. We believe genetic algorithms would be a good fit, our agents become our population, and our performance metrics the measures of fitness. The first implementation we plan would be to explore the fov framework. We would generate individuals with random $\mathrm{r_{avoid}}$, $\mathrm{r_{align}}$, $\mathrm{r_{fov}}$, θ_{fov} and ϕ_{fov} values. Then through multiple iterations, and we would find optimum solutions for collective motion. We plan to add noise and distributions to these solutions to explore how heterogeneity could improve our solutions. We have started developing an analytic tool designed to track the average positions of individuals in the swarm, relative to their group. We believe that sensing ability may influence swarm positioning, as such, we would analyse how fov influences this. We also starting exploring information transfer in terms of how agents avoid obstacles. Preliminary results for this analysis can be found in [Fig.28]. The destination of this further work is to adapt our findings into control strategies for multi-agent robotic platforms. Developing low-cost bio-inspired collective motion strategies to be used in aquatic robots or drones would be the desired outcome from our research.

References

[1] C. W. Clark and M. Mangel, "Foraging and flocking strategies: Information in an uncertain environment.," *American Naturalist*, vol. 123, pp. 626–641, 5 1984, ISSN: 00030147. DOI: 10.1086/284228. [Online]. Available: https://www.jstor.org/stable/2461242.

[2] V. Guttal and I. D. Couzin, "Social interactions, information use, and the evolution of collective migration," *Proceedings of the National Academy of Sciences*, vol. 107, pp. 16 172–16 177, 37 Sep. 2010, ISSN: 0027-8424. DOI: 10.1073/pnas.1006874107. [Online]. Available: https://www.pnas.org/content/107/37/16172%20https://www.pnas.org/content/107/37/16172.abstract%20http://www.pnas.org/cgi/doi/10.1073/pnas.1006874107.

[3] T. D. Seeley, P. K. Visscher, and K. M. Passino, "Group in honey decision bee making swarms when 10 , 000 bees go house hunting , how do they new nesting site ? choose their cooperatively," *American Scientist*, vol. 94, pp. 220–229, 3 2013. DOI: 10.2307/27858770. [Online]. Available: http://www.jstor.org/stable/27858770.

[4] H. Abelson, J. Beal, and G. J. Sussman, *Amorphous computing*, May 2012. DOI: 10.1007/978-1-4614-1800-9_11. [Online]. Available: https://go.gale.com/ps/i.do?p=AONE&sw=w&issn=00010782&v=2.1&it=r&id=GALE7CA62355860&sid=googleScholar&linkaccess=fulltext%20https://go.gale.com/ps/i.do?p=AONE&sw=w&issn=00010782&v=2.1&it=r&id=GALECA62355860&sid=googleScholar&linkaccess=abs.

[5] S. K. M. Yi, M. Steyvers, M. D. Lee, and M. J. Dry, "The wisdom of the crowd in combinatorial problems," *Cognitive Science*, vol. 36, pp. 452–470, 3 Apr. 2012, ISSN: 03640213. DOI: 10.1111/j.1551-6709.2011.01223.x. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/22268680/.

[6] A. Gomez-Marin and Y. Zhang, "Editorial: Emergent behavior in animal-inspired robotics," *Frontiers in Neurorobotics*, vol. 16, 2022, ISSN: 1662-5218. DOI: 10.3389/fnbot.2022.861831. [Online]. Available: https://www.frontiersin.org/article/10.3389/fnbot.2022.861831.

[7] E. Şahin, "Swarm robotics: From sources of inspiration to domains of application," vol. 3342, Springer Verlag, 2005, pp. 10–20. DOI: 10.1007/978-3-540-30552-1_2. [Online]. Available: http://www.kovan.ceng.metu.edu.tr.

[8] J. Halloy, G. Sempo, G. Caprari, *et al.*, "Social integration of robots into groups of cockroaches to control self-organized choices," *Science*, vol. 318, pp. 1155–1158, 5853 Nov. 2007, ISSN: 00368075. DOI: 10.1126/science.1144259. [Online]. Available: www.sciencemag.org/cgi/content/full/318/5853/1150/DC1.

[9] J. E. Herbert-Read, A. Perna, R. P. Mann, T. M. Schaerf, D. J. T. Sumpter, and A. J. W. Ward, "Inferring the rules of interaction of shoaling fish," *Proceedings of the National Academy of Sciences*, vol. 108, pp. 18 726–18 731, 46 Nov. 2011, ISSN: 0027-8424. DOI: 10.1073/PNAS.1109355108. [Online]. Available: https://www.pnas.org/content/108/46/18726%20https://www.pnas.org/content/108/46/18726.abstract.

[10] M. Ballerini, N. Cabibbo, R. Candelier, *et al.*, "Interaction ruling animal collective behavior depends on topological rather than metric distance: Evidence from a field study," *Proceedings of the National Academy of Sciences*, vol. 105, pp. 1232–1237, 4 Jan. 2008, ISSN: 0027-8424. DOI: 10.1073/pnas.0711437105. [Online]. Available: https://www.pnas.org/content/105/4/1232%20https://www.pnas.org/content/105/4/1232.abstract%20www.pnas.org/cgi/content/full/%20http://www.pnas.org/cgi/doi/10.1073/pnas.0711437105.

[11] D. J. Sumpter, J. Krause, R. James, I. D. Couzin, and A. J. Ward, "Consensus decision making by fish," *Current Biology*, vol. 18, pp. 1773–1777, 22 Nov. 2008, ISSN: 09609822. DOI: 10.1016/j.cub.2008.09.064.

[12] G. Grégoire, H. Chaté, and Y. Tu, "Moving and staying together without a leader," *Physica D: Nonlinear Phenomena*, vol. 181, pp. 157–170, 3-4 Jan. 2003, ISSN: 01672789. DOI: 10.1016/S0167-2789(03)00102-7. [Online]. Available: http://arxiv.org/abs/cond-mat/0401257%20http://dx.doi.org/10.1016/S0167-2789(03)00102-7.

[13] C. W. Reynolds, “Flocks, herds and schools: A distributed behavioral model,” *ACM SIGGRAPH Computer Graphics*, vol. 21, pp. 25–34, 4 1987, ISSN: 00978930. DOI: 10.1145/37402.37406. [Online]. Available: http://portal.acm.org/citation.cfm?doid=37401.37406%20http://portal.acm.org/citation.cfm?doid=37402.37406.

[14] F. J. Heras, F. Romero-Ferrero, R. C. Hinz, and G. G. D. Polavieja, “Deep attention networks reveal the rules of collective motion in zebrafish,” *PLoS Computational Biology*, vol. 15, e1007354, 9 2019, ISSN: 15537358. DOI: 10.1371/journal.pcbi.1007354. [Online]. Available: https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1007354.

[15] I. D. COUZIN, J. KRAUSE, R. JAMES, G. D. RUXTON, and N. R. FRANKS, “Collective memory and spatial sorting in animal groups,” *Journal of Theoretical Biology*, vol. 218, pp. 1–11, 1 Sep. 2002, ISSN: 00225193. DOI: 10.1006/jtbi.2002.3065. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0022519302930651.

[16] A. Huth and C. Wissel, “The simulation of the movement of fish schools,” *Journal of Theoretical Biology*, vol. 156, pp. 365–385, 3 Jun. 1992, ISSN: 00225193. DOI: 10.1016/S0022-5193(05)80681-2. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0022519305806812.

[17] S. J. Simpson, G. A. Sword, P. D. Lorch, and I. D. Couzin, “Cannibal crickets on a forced march for protein and salt,” *Proceedings of the National Academy of Sciences of the United States of America*, vol. 103, pp. 4152–4156, 11 Mar. 2006, ISSN: 00278424. DOI: 10.1073/pnas.0508915103. [Online]. Available: https://www.pnas.org/content/103/11/4152%20https://www.pnas.org/content/103/11/4152.abstract.

[18] J. Werfel, K. Petersen, and R. Nagpal, “Designing collective behavior in a termite-inspired robot construction team,” *Science*, vol. 343, pp. 754–758, 6172 Feb. 2014, ISSN: 10959203. DOI: 10.1126/science.1245842. [Online]. Available: http://www.ncbi.nlm.nih.gov/pubmed/24531967.

[19] S. Bernardi, A. Colombi, and M. Scianna, “A discrete particle model reproducing collective dynamics of a bee swarm,” *Computers in Biology and Medicine*, vol. 93, pp. 158–174, Feb. 2018, ISSN: 18790534. DOI:

10.1016/j.compbiomed.2017.12.022. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0010482517304195.

[20] R. Lukeman, Y. X. Li, and L. Edelstein-Keshet, "Inferring individual rules from collective behavior," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 107, pp. 12 576–12 580, 28 Jul. 2010, ISSN: 00278424. DOI: 10.1073/pnas.1001763107. [Online]. Available: https://www.pnas.org/content/107/28/12576%20https://www.pnas.org/content/107/28/12576.abstract.

[21] J. Krause, G. D. Ruxton, G. Ruxton, and I. G. Ruxton, *Living in groups - jens krause, professor of fish biology and ecology jens krause, graeme d. ruxton, graeme ruxton, ibls graeme ruxton - google books*, 2002. [Online]. Available: https://books.google.co.uk/books?hl=en&lr=&id=HAoUFfVFtMcC&oi=fnd&pg=PA1&ots=mn0IeBa8i5&sig=7mcEOIMFoXX8Qqowem-rN2F4WIA&redir_esc=y#v=onepage&q&f=false%20https://books.google.com/books?hl=en&lr=&id=HAoUFfVFtMcC&oi=fnd&pg=PA1&dq=info:CUSGM6JlUeAJ:scholar.goo.

[22] Vicsek, Czirók, Ben-Jacob, Cohen, and Shochet, "Novel type of phase transition in a system of self-driven particles.," *Physical review letters*, vol. 75, pp. 1226–1229, 6 Aug. 1995, ISSN: 1079-7114. DOI: 10.1103/PhysRevLett.75.1226. [Online]. Available: https://journals.aps.org/prl/abstract/10.1103/PhysRevLett.75.1226%20https://link.aps.org/doi/10.1103/PhysRevLett.75.1226%20http://www.ncbi.nlm.nih.gov/pubmed/10060237.

[23] H. Kunz and C. K. Hemelrijk, "Artificial fish schools: Collective effects of school size, body size, and body form," *Artificial Life*, vol. 9, pp. 237–253, 3 Jun. 2003, ISSN: 10645462. DOI: 10.1162/106454603322392451. [Online]. Available: http://direct.mit.edu/artl/article-pdf/9/3/237/1662066/106454603322392451.pdf.

[24] J. H. Tien, S. A. Levin, and D. I. Rubenstein, "Dynamics of fish shoals: Identifying key decision rules," *Evolutionary Ecology Research*, vol. 6, pp. 555–565, 4 2004, ISSN: 15220613.

[25] S. V. Viscido, J. K. Parrish, and D. Grünbaum, "The effect of population size and number of influential neighbors on the emergent properties of fish schools," *Ecological Modelling*, vol. 183, pp. 347–363, 2-3 Apr.

2005, ISSN: 03043800. DOI: 10.1016/j.ecolmodel.2004.08.019. [Online]. Available: https://linkinghub.elsevier.com/retrieve/pii/S0304380004004958.

[26] A. Cavagna, A. Cimarelli, I. Giardina, *et al.*, "Scale-free correlations in starling flocks," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 107, pp. 11 865–11 870, 26 Jun. 2010, ISSN: 00278424. DOI: 10.1073/pnas.1005766107. [Online]. Available: https://www.pnas.org/content/107/26/11865%20https://www.pnas.org/content/107/26/11865.abstract.

[27] Y. Katz, K. Tunstrøm, C. C. Ioannou, C. Huepe, and I. D. Couzin, "Inferring the structure and dynamics of interactions in schooling fish," *Proceedings of the National Academy of Sciences of the United States of America*, vol. 108, pp. 18 720–18 725, 46 Nov. 2011, ISSN: 10916490. DOI: 10.1073/pnas.1107583108. [Online]. Available: www.pnas.org/cgi/doi/10.1073/pnas.1107583108%20https://pubmed.ncbi.nlm.nih.gov/21795604/.

[28] T. Niizato and Y. P. Gunji, "Fluctuation-driven flocking movement in three dimensions and scale-free correlation," *PLoS ONE*, vol. 7, e35615, 5 May 2012, ISSN: 19326203. DOI: 10.1371/journal.pone.0035615. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0035615.

[29] W. H. Warren, "Collective motion in human crowds," *Current Directions in Psychological Science*, vol. 27, pp. 232–240, 4 Jul. 2018, ISSN: 14678721. DOI: 10.1177/0963721417746743. [Online]. Available: https://journals.sagepub.com/doi/full/10.1177/0963721417746743.

[30] K. Ried, T. Müller, and H. J. Briegel, "Modelling collective motion based on the principle of agency: General framework and the case of marching locusts," *PLoS ONE*, vol. 14, e0212044, 2 Feb. 2019, ISSN: 19326203. DOI: 10.1371/journal.pone.0212044. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0212044.

[31] L. Li, M. Nagy, J. M. Graving, J. Bak-Coleman, G. Xie, and I. D. Couzin, "Vortex phase matching as a strategy for schooling in robots and in fish," *Nature Communications*, vol. 11, pp. 1–9, 1 Dec. 2020, ISSN: 20411723. DOI: 10.1038/s41467-020-19086-0. [Online]. Available: https://doi.org/10.1038/s41467-020-19086-0.

[32] S. Abar, G. K. Theodoropoulos, P. Lemarinier, and G. M. O'Hare, *Agent based modelling and simulation tools: A review of the state-of-art software*, 2017. DOI: 10.1016/j.cosrev.2017.03.001. [Online]. Available: www.elsevier.com/locate/cosrev.

[33] *Comses net*, 2018. [Online]. Available: https://www.comses.net/.

[34] Modelling4All, "Behaviour composer version 2.0," 2010. [Online]. Available: https://www.m.modelling4all.org..

[35] J. Klein, "Breve simulator version 2.7.2," 2015. [Online]. Available: https://www.spiderland.org..

[36] T. E. Gorochowski, A. Matyjaszkiewicz, T. Todd, *et al.*, "Bsim: An agent-based tool for modeling bacterial populations in systems and synthetic biology," *PLoS ONE*, vol. 7, e42790, 8 Aug. 2012, ISSN: 19326203. DOI: 10.1371/journal.pone.0042790. [Online]. Available: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0042790.

[37] R. Sienkiewicz, "Digi hive version 110304," 2019. [Online]. Available: https://www.digihive.pl..

[38] STFC, "Flexible large-scale agent modelling environement, version 0.17.1," 2013. [Online]. Available: https://www.flame.ac.uk..

[39] QosCosGrid, "Gridabm," 2010. [Online]. Available: https://www.gridabm.soundforge.net..

[40] A. N. Laboratory, "Repast simphony version 2.8.0," 2020. [Online]. Available: https://www.repast.github.io..

[41] Swarm, "Swarm version 2.2," 2020. [Online]. Available: https://www.repast.github.io..

[42] U. Technologies, "Unity engine version 2021.1.19," 2021. [Online]. Available: https://www.unity.com..

[43] E. Games, "Unreal engine version 4.27," 2021. [Online]. Available: https://www.unrealengine.com.

[44] K. Ohnishi, A. Takahashi, H. Tanaka, and T. Ohnishi, "Relationship between frequency of upside-down posture and space size around upside-down catfish, ¡i¿synodontis nigriventris¡/i¿," *Biological Sciences in Space*, vol. 10, no. 4, pp. 247–251, 1996. DOI: 10.2187/bss.10.247.

[45] N. Meyer-Vernet and J.-P. Rospars, "How fast do living organisms move: Maximum speeds from bacteria to elephants and whales," *American Journal of Physics*, vol. 83, pp. 719–722, 8 Aug. 2015, ISSN: 0002-9505. DOI: 10.1119/1.4917310.

[46] A. B. Kao, N. Miller, C. Torney, A. Hartnett, and I. D. Couzin, "Collective learning and optimal consensus decisions in social animal groups," *PLoS Computational Biology*, vol. 10, 8 2014, ISSN: 15537358. DOI: 10.1371/journal.pcbi.1003762.

[47] D. Pita, B. A. Moore, L. P. Tyrrell, and E. Fernández-Juricic, "Vision in two cyprinid fish: Implications for collective behavior," *PeerJ*, vol. 2015, e1113, 8 Aug. 2015, ISSN: 21678359. DOI: 10.7717/peerj.1113. [Online]. Available: https://peerj.com/articles/1113.

[48] B. L. Partridge and T. J. Pitcher, "The sensory basis of fish schools: Relative roles of lateral line and vision," *Journal of Comparative Physiology*, vol. 135, pp. 315–325, 4 Dec. 1980, ISSN: 03407594. DOI: 10.1007/BF00657647. [Online]. Available: https://link.springer.com/article/10.1007/BF00657647.

[49] R. M'Hallah, A. Alkandari, and N. Mladenovic, "Packing unit spheres into the smallest sphere using vns and nlp," *Computers and Operations Research*, vol. 40, no. 2, pp. 603–615, 2013, ISSN: 0305-0548. DOI: https://doi.org/10.1016/j.cor.2012.08.019. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S030505481200192X.

[50] B. Shang, R. Crowder, and K. P. Zauner, "Simulation of hardware variations in swarm robots," 2013, pp. 4066–4071, ISBN: 9780769551548. DOI: 10.1109/SMC.2013.694.

[51] M. Ester, H.-P. Kriegel, J. Sander, and X. Xu, "A density-based algorithm for discovering clusters in large spatial databases with noise," 1996, pp. 226–231. [Online]. Available: www.aaai.org.

[52] C. A. Yates, R. Erban, C. Escudero, *et al.*, "Inherent noise can facilitate coherence in collective swarm motion," *Proceedings of the National Academy of Sciences*, vol. 106, pp. 5464–5469, 14 Apr. 2009, ISSN: 0027-8424. DOI: 10.1073/pnas.0811195106. [Online]. Available: https://www.pnas.org/content/106/14/5464%20https://www.pnas.org/content/106/14/5464.abstract%20http://www.pnas.org/cgi/doi/10.1073/pnas.0811195106.

[53] H. Singh, M. M. Gupta, T. Meitzler, *et al.*, *Real-life applications of fuzzy logic*, 2013. DOI: 10.1155/2013/581879. [Online]. Available: http://www.hindawi.com/journals/afs/2013/581879/.

[54] D. Knebel, C. Sha-ked, N. Agmon, G. Ariel, and A. Ayali, "Collective motion as a distinct behavioral state of the individual," *iScience*, vol. 24, no. 4, p. 102 299, 2021, ISSN: 2589-0042. DOI: https://doi.org/10.1016/j.isci.2021.102299. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2589004221002674.

[55] L. U. Sneddon, "The bold and the shy: Individual differences in rainbow trout," *Journal of Fish Biology*, vol. 62, pp. 971–975, 4 Apr. 2003, ISSN: 00221112. DOI: 10.1046/j.1095-8649.2003.00084.x. [Online]. Available: https://onlinelibrary.wiley.com/doi/full/10.1046/j.1095-8649.2003.00084.x%20https://onlinelibrary.wiley.com/doi/abs/10.1046/j.1095-8649.2003.00084.x%20https://onlinelibrary.wiley.com/doi/10.1046/j.1095-8649.2003.00084.x.

[56] R. C. Arkin, "Motor schema based mobile robot navigation," *The International Journal of Robotics Research*, vol. 8, pp. 112–92, 1989.

[57] D. Payton, "An architecture for reflexive autonomous vehicle control," vol. 3, pp. 1838–1845, 1986. DOI: 10.1109/ROBOT.1986.1087458.

[58] R. Brooks, "A robust layered control system for a mobile robot," *IEEE Journal on Robotics and Automation*, vol. 2, no. 1, pp. 14–23, 1986. DOI: 10.1109/JRA.1986.1087032.

[59] J. D. Davidson, M. M. Sosna, C. R. Twomey, V. H. Sridhar, S. P. Leblanc, and I. D. Couzin, "Collective detection based on visual information in animal groups," *Journal of the Royal Society, Interface*, vol. 18, p. 20 210 142, 180 2021, ISSN: 17425662. DOI: 10.1098/rsif.2021.0142. [Online]. Available: https://doi.org/10.1101/2021.02.18.431380.

[60] A. Berdahl, C. J. Torney, C. C. Ioannou, J. J. Faria, and I. D. Couzin, "Emergent sensing of complex environments by mobile animal groups," *Science*, vol. 339, pp. 574–576, 6119 Feb. 2013, ISSN: 10959203. DOI: 10.1126/science.1225883. [Online]. Available: http://science.sciencemag.org/.

[61] V. Braitenberg, "Vehicles: Experiments in synthetic psychology," 1986.