Heterogenous Swarming and Emerging Collective Motion of RVR and BOLT Robots:

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**Abstract**

**Swarming intelligence > swarms > boid > heterogeneous vs homogeneous > formations and collective motion > so what**

CONTENTS:

[Heterogenous Swarming and Emerging Collective Motion of RVR and BOLT Robots: 1](#_Toc166623740)

[I. Introduction 1](#_Toc166623741)

[II. Background Info 2](#_Toc166623742)

[A. Boid Swarming Algorithm 2](#_Toc166623743)

[B. Emergent Collective Motion 2](#_Toc166623744)

[III. Literature Review 2](#_Toc166623745)

[A. The Boid Model and Swarm Formations 2](#_Toc166623746)

[B. Applications of Heterogeneous Swarms 2](#_Toc166623747)

[C. Benefits of Heterogeneous Swarms 3](#_Toc166623748)

[D. Autonomous Emergent Collective Behaviour 3](#_Toc166623749)

[IV. Planning 3](#_Toc166623750)

[A. Project Plan 3](#_Toc166623751)

[B. Potential Difficulties 4](#_Toc166623752)

[V. Methodology 4](#_Toc166623753)

[A. Research Design 4](#_Toc166623754)

[B. Background Theory and Analysis 5](#_Toc166623755)

[VI. Current Progress 5](#_Toc166623756)

[C. Sphero BOLT and RVR capabilities 5](#_Toc166623757)

[D. Sphero BOLT and RVR Communications 6](#_Toc166623758)

[E. Swarming with Vicon 6](#_Toc166623759)

[F. Collective Motion in Simulation 6](#_Toc166623760)

[VII. Future Work 7](#_Toc166623761)

[A. Further Development, Testing and Validation 7](#_Toc166623762)

[B. Implement Emergent Collective Motion 7](#_Toc166623763)

[C. Extension: Asymmetric Behaviour 7](#_Toc166623764)

[D. Extension: Heterogeneous Plug and Play 7](#_Toc166623765)

[VIII. Conclusion 7](#_Toc166623766)

[References: 8](#_Toc166623767)

# Introduction

As the field of robotics moved forward with advances in both the efficiency and capability of embedded systems utilised in robots so did the scope extend for robots to tackle an ever-growing set of larger and more complex challenges. An approach to these new challenges can be made through the implementation of swarm robotics, which is a branch of multi-agent robotics systems that is characterized by its emphasis towards the emulation of natural biological swarms, such as packs of wolves hunting prey; multi-agent swarms utilise a multitude of smaller and simpler agents that act together towards a collective intent.

While many classical tasks of robotics swarms, which are loosely based on patterns found in nature, such as path finding, source localization and area exploration and coverage. Furthermore nature utilizes collective motion and formations optimize efficiency of swarms with the implementation of formation control becoming an increasingly emerging research topic within the field.

While current research within swarm robotics that is aimed towards formation control is modelled, simulated and implemented with the use of homogeneous swarms, formations within heterogeneous swarms is mostly uncovered. Heterogeneous swarming presents an opportunity to broaden the scope and applications of robotic swarms, enabling robots with differing degrees of computational power, capabilities, sensors and mobility to work together. With the advance of swarm robotics and the increasing complexity required of robot swarms to tackle the challenges presented, physical and behavioural heterogeneity within swarms presents a clear path to extend the capabilities of swarm robotics [1]. To both fully optimize as well as to further understand the opportunities presented by heterogeneous swarms it is important to research their full capabilities and limitations.

Hence the aim of this research project is to enact the synthesis of existing knowledge, models and implementations into a functioning heterogeneous swarm of robots that displays emergent collective motion, this brings forward new opportunities within the field of swarm robotics for the research, manipulation and application of heterogeneous swarms.

# Background Info

## Boid Swarming Algorithm

The **boids** model was initially conceptualised by Craig Reynolds in 1986, which simulated the flocking motions of birds,

## Emergent Collective Motion

# Literature Review

## The Boid Model and Swarm Formations

Swarm robotics is defined and characterized by its attempt to emulate the swarm intelligences seen in the natural world through the lens of robotics; robots interact on a local level with simple rules, through this it is possible to design collective behaviors which are both scalable and robust [1]. One of the approaches towards this is the Boids Swarming model, which was originally conceptualized by Craig Reynolds in 1986, it sought to model the flocking of birds through a set of rules: separation – boids must not move too close to each other to avoid collisions, alignment – boids must move in the general direction of the rest of the flock, and cohesion – boids must move towards the center of the flock. By implementing these three rules Reynolds created a simulation that modelled the flocking of birds [2]. While Reynolds’ work in 1987 was centered from the view of computer graphics, the Boids model proved useful in the understandings of swarm intelligence and was first realized in the realm of robotics by Turgut et al. who developed a system for robots to determine the heading, position and velocity of their peers thus enabling them to form “flocking” swarms utilizing the Boid rules of separation, cohesion and alignment [3].

Collective behaviour within swarm intelligence is crucial to the real-world application and control of swarms, by being able to understand the swarm as a collective it allows for the manipulation of a swarm to a collective task or goal. A key form of this is in creating defined formations. In recent history this challenge has been approached in many ways, however this project aims to provide an extension of the existing formation control methods through the application to the real world in readily accessible and low complexity robotics, which present both easy access research [4], [5], practical [6] and educational opportunities [7]. Emergent behaviors of formations in swarms proves desirable as it seeks to provide swarms with optimal positioning for various tasks while maintaining the robustness and scalability of the swarm model. In the past swarming formations have been achieved through a variety of different methods, however many of these methods relied fully or partially on central controllers [8], [9], [10], this reduces the robustness and scalability of the swarm, additionally there have been many decentralized based approaches, those that utilised different forms machine learning through the use of a graphical/potential field type techniques seen in [11], [12], [13]. In addition to this there exists some prevailing research into formation control through emergent behaviours, which are implemented in a variety of methods seen in [14], [15]. These methods exist as a large wealth of knowledge in the development and implementation of swarming formation control systems.

However the current research into collective motions within swarm robotics is pervaded by the use of homogeneous swarms [14], [15], with the new research presented in this thesis, we utilise reinforcement learning in simulation and apply this to real robots to create completely emergent collective motion within heterogeneous swarms. This differs to the types of collective motion that currently exist, with classical formation control systems utilizing an overlaying algorithms or parametric rules, such as Hüttenrauch et al. [16], who controlled the entire swarm through the use of deep reinforcement learning, Bezcioglu et al. [17] demonstrates flocking through a global state space matrix utilizing deep reinforcement learning, Egerstedt and Hu [18] utilised a coordinated control scheme to create path following to a virtual leader within a multi agent system. In contrary to these approaches the emergent collective motion within this project refers to the type of behaviours achieved through only the modification of the swarm parameters; behaviour which emerges from this effect, for instance Khan et al. [19] utilised an evolutionary approach to achieve a set of emergent collective behaviours through the modification of these parameters through the use of reinforcement learning, this concept was pushed further by Abpeikar et al. [20] where the behaviours were further developed, tuned and implemented in both simulation through CoppeliaSim environment and real world applications using Sphero BOLTs.

Hence these papers show that not only is there significant interest and investment in the conceptualization and realization of swarming formations through a variety of different approaches, this research project proposes the use of reinforcement learning to bootstrap emergent collective behaviours within simulation based on the paper by Abpeikar et al. [20] and to reproduce this within heterogeneous swarms.

## Applications of Heterogeneous Swarms

Throughout nature both homogeneous and heterogeneous swarms develop to solve distinct and unique problems [21], [22], these are emulated within swarm robotics, with many papers demonstrating swarms of robots solving natural problems with key benefits being those of robustness, flexibility and scalability [6], [23], [24], [25], [26], [27]. These key features of swarming homogeneous and heterogeneous systems make them well suited to solving novel challenges and scenarios that traditional single and multi-agent systems do not perform as well in. Swarm robotics can be applied to a multitude of different applications, the applications that are typically well suited to this are ones that cover regions, involve high risk, scale up or down in time required, or in applications that required redundancy [27]. For example, swarm robotics have been increasingly researched as a useful asset in mine clearing, this is due to both the high risk and large time and size scales, as minefields are both vast but also having by having a large swarm accidental mine detonations do not result in significant losses to a project’s capability [28], heterogeneity could be applied to this through utilizing more complex drones to perform mission planning while swarms are used to collect data on a smaller scale.

Both physical and behavioural heterogeneity within swarms opens up new dimensions in terms of capabilities and possibilities for swarm intelligence [29]. While hallmark papers such as Swarmanoid [30] conceptualize and implement models for some of the possible applications of heterogeneous swarms, formation control is a key element to the application of heterogeneous swarms with formations providing added stability, efficiency and task – based optimization to swarms. Recent research has shown success in formations and collective motion of heterogeneous swarms with differing levels of diversity within the swarm populations [31], [32], [33]. However, many of these heterogeneous swarm formations implement centralized, semi-centralized or computationally heavy decentralized formations in comparison to the implementations presented in this research project.

To introduce emergent collective behaviour this project will utilise prior research done using homogeneous swarms. Boid rule parameters were modified using reinforcement learning to generate emergent collective behaviours [20], within the paper by Abpeikar et al. this is shown to be a viable implementation within simulation with the use of a homogeneous swarm and thus proves promising for adaptation to a heterogeneous swarm in similar conditions.

## Benefits of Heterogeneous Swarms

Swarm intelligence and robotics is heavily steeped in the thought of biomimicry, a practice that seeks to learn and copy nature to solve a variety of problems, with many problems having existed in nature and with the evolution of swarm behaviour within less singularly cognitive species, these provide an example to how lower complexity robots can complete challenges requiring higher level thinking through collective behaviour [34]. While studies are largely dominated with the use of homogeneous swarms [1], the idea of heterogeneous swarms, swarms made of different types of robots, has become increasingly researched in recent times as the challenges posed to robotic swarms have evolved [35]. An approach to the widely opened horizons of heterogeneous swarming can be seen within the experiment by Dorigo et al. [30], where three different classes of robots, “eye”, “hand” and “foot” robots, in which different elements of the swarm provide significantly different and more capabilities to the heterogeneous swarm over that of a homogenous swarm, other novel approaches to develop useful heterogeneous swarms include ones utilizing a “shepherding” method in which powerful, less mobile robots collect and slave groups of less powerful, more mobile robots [36], synergizing the benefits robustness and scalability of swarm robotics with the complexity and power of classical single agent systems. Furthermore, it has been demonstrated by Prorok et al. that heterogeneous swarms can use decentralized control to divide and conquer across multiple ‘species’ specific tasks, which shows how larger heterogeneous swarms can provide significantly more modularity and the ability to solve multiple problem types simultaneously [33].

Collective motion within swarms can provide both crucial placements to optimize efficiency as well as organization within swarms, this is particularly crucial to heterogeneous swarming. These could be seen useful across a multitude of conceptual heterogeneous swarm applications such as **talk more about the applications of heterogeneous swarms here and how these benefits can apply [was struggling to find actual sources on heterogeneous swarms being used in real life]**

## Autonomous Emergent Collective Behaviour

While emergent collective behaviour, particularly collective motion bears a resemblance to formation control methods mentioned above, emergent collective behaviour differs through the methodology of achieving it. B

# Planning

## Project Plan

The project’s upcoming deliverables are the interim report, viva voce and project seminar, due on 17 May 2024 and 28 May 2024 respectively. The remainder of the project’s timeline is dictated in Appendix [ insert gantt chart] which shows a Gantt chart of different tasks required as well as their beginning and expected completion dates. This timeline was designed with the efficient and thorough completion of the project deliverables by the 25 Oct 2024, which entails the submission of python code package, documentation as well as a summary report, by aiming to finish this by the 1 Oct 2024 this allows the possibility for either polishing of the final submission or to work on potential extensions before the due date. To maximise the efficiency towards completing the project the tasks are placed in both a sequential and logical order as well as in parallel to ensure that during particular weeks it is possible to complete tasks that required lab access, such as testing, debugging and datalogging that requires Vicon as well as completing tasks outside of lab hours such as simulations, code development or optimization and analysis of results as well as literature review.

The project is effectively approached in two phases:

1. **Phase 1: BOLT and RVR Swarm Boid Integration:** Review and understand existing RVR and BOLT swarming codes, modify and develop code to connect Bolt as a boid agent to the code. Validate swarm formation through Vicon tracking and debug console.
2. **Phase 2: Heterogeneous Formations:** Research, review and develop emergent collective motion for RVR and BOLT swarm to form multiple different heterogeneous formations through the implementation of reinforcement learning developed rules.

The practical element of this research project will entail the material requirements of Sphero Bolt and RVR robots to form a heterogeneous swarm. The Bolt robots run standalone off Bluetooth, however the RVR robots require the use of Raspberry Pi 3B+ single board computers to control them. Additionally, the research project also requires the use of the Vicon system for both datalogging and code function, these materials are pre-existing and/or on loan from UNSW Canberra thus the project will require no significant budget.

## Potential Difficulties

As the research project entails a practical component the nature of the project may evolve as certain different limitations come into play. These could appear within any stage of the project, simulations, design, testing and validation all have the potential reveal possible limitations. Additionally, there may be further project difficulties as the practical nature of the project adds to a variable of uncertainty. With any heterogeneous system of robots there are multiple challenges that arise within the development cycle those that are particular to this research project are:

Delays in the completion of tasks resulting in overall right-shifting of the timeline, this can result from issues such as additional testing and debugging being required as well as faulty, damaged or missing hardware requiring repair, replacement or purchase.

Initial difficulty in understanding, modifying and implementing existing swarming code as well as time required to further understand code to debug.

Bluetooth and Vicon integration may require more powerful hardware as well as extending troubleshooting time.

Compatibility issues may arise between RVR mounted Raspberry Pi 3B+’s and Bolts.

By having a good situational awareness of the possible difficulties that may be encountered within this research project, these difficulties can be mitigated through a variety of precautionary measures to avoid issues during the progress of the research project:

1. Tracking tasks allows for both pre-planning and insights into current progress for task completion, this will result in less delays and keep progression through milestones timely.
2. By consulting with subject matter experts on the code base (thesis supervisors) as well as using up-to-date libraries the impact of this potential project difficulty can be mitigated
3. Testing data rates and reliability and consistency of connection early on, to discover what issues may arise as the project progresses.
4. Testing connections before beginning of running main code, implementation of alternative and contingency methods for Bluetooth.

Through the implementation of these strategies, as well as maintaining a good level of situational awareness, the potential difficulties mentioned above should be addressed and mitigated to a degree of acceptability, this is to ensure both the efficiency and thoroughness of the project.

# Methodology

## Research Design

The main objective of this research project is to achieve heterogeneous swarm formations using Sphero BOLT and RVR robots. In order to achieve this, thorough research and a literature review have been conducted to analyse and understand different kinds of swarming and formation control in both homogeneous and heterogeneous swarms to gain background knowledge and a point of refence in the design and implementation of heterogeneous swarm formations.

## Background Theory and Analysis

Within the Boid swarming model, individual agents move with reference to the rest of the swarm, this is achieved through three fundamental forces: separation, cohesion and alignment [2].

* **Separation:** move away from nearby agents to prevent collision

A circular object with arrows pointing to the center

Description automatically generated with medium confidence

Figure 1A: Separation Diagram [2]

* **Alignment:** move towards the average heading of nearby agent

A clock with arrows pointing at the time

Description automatically generated

Figure 1B: Alignment Diagram [2]

* **Cohesion:** move towards the average position of swarm (center of swarm)

A circular object with arrows and triangles

Description automatically generated

Figure 1C: Alginment Diagram [2]

Figures above are exactly reused and made by Craig Reynolds. [2]

Each fundamental swarming force has additional Boid and situational awareness parameters [19], [37], these are:

* **Wₛ, Wₐ, Wₓ:** Weights for separation, alignment, and cohesion
* **Vₘₐₓ, Vₘᵢₙ:** Maximum and minimum velocity
* **Rₛ, Rc, Rₐ:** Separation radius, cohesion radius, and alignment radius

By modifying these parameters it is possible to create emergent behaviours resulting in collective motion, shown by Khan et al. and Abpeikar et al. [19], [20], as discussed within the literature review. These formations

# Current Progress

## Sphero BOLT and RVR capabilities

The Sphero BOLT and RVR are both low cost consumer grade products produced by the Sphero company, while sharing large parts of both their hardware, software and firmware the robots have differing capabilities in regards to both their sensors and effectors [38], [39], [40].

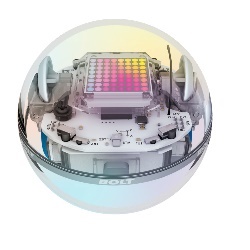
 

Figure 2A (left) and Figure 2B (right): Sphero BOLT (left) and RVR (right)

The BOLT (figure 2A) is a robot that operates within a spherical housing it communicates with the RVR via Bluetooth. It has 2 drive motors with encoders and a sensor suite consisting of a light sensor to detect ambient light between 0 – 100,000 lux, four infrared emitter and receiver pairs for communication with other Sphero products, an inertial measurement unit which consists of an accelerometer, gyro and magnetometer which is used to read the robots acceleration and heading to then calculate velocity and position through dead reckoning [38].

The other agent utilised in the heterogeneous swarm is the Sphero RVR with a Raspberry Pi 3B+, the Raspberry Pi communicates with RVR utilizing a USB A for 5V power, as well as the UART GPIO pins on the Raspberry Pi for communication. The Sphero RVR utilizes 2 drive motors with encoders that are controlled through a drive controller utilizing a skid steer drive motion. The RVR also has a sensor suite with a similarly constructed IMU to the BOLT while also incorporating a colour detection sensor and ambient light sensor [40].

To effectively operate both RVR and BOLT in conjunction with each other and to avoid the inherent errors that develop throughout the experiment run time using the IMU system, the Vicon system is used, the UNSW Canberra RAS Laboratory Vicon system consists of 12 cameras that use vision processing to create a GPS – like system within the laboratory environment [41].

While both robots are produced by Sphero, utilizing many identical control schemes, sensors, firmware and APIs [38], [39], [40], there are many innate challenges presented by the research project’s goal to integrate both robots within a heterogeneous swarm. Both agents differ within their software capabilities, with the RVR having significantly more control over data, as well as being equipped with a significantly more powerful Raspberry Pi with it’s on GPIO pins [42]. In contrast to this the Sphero BOLT does not have any local operating system, and instead runs completely off the Raspberry Pi via Bluetooth, only being able to send data and receive commands from the RVR mounted Raspberry Pi. These challenges will dictate a wide variety of design choices made in order to successfully complete the research project such as overall system communications scheme (figure 3) as well as the final structures of emergent collective motion.

## Sphero BOLT and RVR Communications

The initial investigation into communications between the Sphero BOLT and RVR showed promise within two different communications protocols: Bluetooth and Infrared.

* **Bluetooth:** through use of the python ‘bleak’ library, which provides a client agnostic Bluetooth service, the SpheroV2 library can be used to send commands and receive data directly from the Raspberry Pi mounted on the RVR, this allows the Raspberry Pi to effectively ‘host’ the BOLT as an Agent object [38], [39], [43].
* **Infrared:** the Sphero BOLT and RVR both within their sensor suites, include a set of **four** IR transmitter and receiver pairs, however the SpheroV2 library documentation indicated that there was a low level of integration of the infrared communication within the library, with the transmission being locked down to simple on/off signals and without extensive work and a deep dive into the firmware of the BOLT robot, it would be impossible to implement any type of transmission protocol that extended beyond a cumbersome and high bit error rate top – level on – off keying implementation [38], [39].

Hence the conclusion was made that in order to establish communications between the Sphero BOLT and RVR, Bluetooth 4.0+ is required, this was initially tested with the Raspberry Pi’s onboard Bluetooth device. Throughout the implementation of this it was found that the PyPI (pip) install of the bleak library required extended troubleshooting as well as in some cases the Bluetooth service was not able to be started within the Raspbian OS environment (known issue). A current alternative to this was to utilise a Bluetooth USB dongle connected to the Raspberry Pi, where the onboard Bluetooth service; explicitly the hciuart service could not be initialized, this is, however, not the case on some Raspberry Pi 3B+’s and requires further investigations and a possible design choice reversal to use a different Debian – based Linux distributions in order to both maintain the readily available Raspberry Pi Debian support while alleviating problems explicitly introduced through the use of Raspbian OS.

To perform a test of this functionality a group of two robots was used comprising of an RVR and BOLT, they both initialized themselves and proceeded to move into a

## Swarming with Vicon

The heterogeneous Boid swarm formation utilizing Vicon fundamentally consists of RVR robots hosting a group of BOLTs across each Raspberry Pi 3B+ utilizing threading to move each robot as if it was an individual agent of the swarm. The term ‘hosting’ refers to the Raspberry Pi handling all of the BOLT’s location data, movement commands as well as communications with other RVRs and BOLTs. To ascertain the BOLT and RVR’s true position within the local positioning system Vicon is used to determine where each robot is currently operating, pictured in figure 3 below is the system architecture diagram which shows the conceptualization of how the total code will work.

A diagram of a company

Description automatically generated

Figure 3: System Architecture Diagram

This data is then sent through a local network connection to the Vicon server which passes this through the ‘vicon\_bridge.py’. This code initializes the Vicon data stream on the server, accessing the Vicon server through the local network, this data is then passed as strings and transmitted through a single pylsl stream, this is done due to the restriction of pylsl streams requiring to be of one data type. This stream was transmitted through a local network connection to the Raspberry Pi mounted on the RVR, which then converts strings back to the original data formats of float32 and string. The data is transmitted using the following scheme:

|  |  |  |  |
| --- | --- | --- | --- |
| **Index** | 0 | 1 | 2 |
| **Data** | X Coordinate | Y Coordinate | ID |

Table 1: Vicon Bridge Stream Data

The Raspberry Pi’s run the script ‘rvr\_swarm\_controller.py’, this script initializes the RVR and BOLTs as **Agent** objects, each Agent object is used to represent a different member of the Boid swarm, with the ‘Boid.py’ and ‘Boids\_Rules.py’ files providing a framework to instantiate each Agent object as a Boid swarm member. Each Agent object is then treated as a separate Boid swarm member, with the control loop taking its location:

* **if RVR location received:** update RVR Agent object and calculate Boid vector, broadcast location to unique known Boid ID over local network.
* **if BOLT location received:** update BOLT Agent object and calculate Boid vector, broadcast location to unique known Boid ID over local network.

This code takes place recursively and allows for each Raspberry Pi to calculate the correct Boid vector for each individual agent, with each Agent method having specific BOLT and RVR code for either robot. This initial build of code was run and did not entirely work. With errors arising from the adaptation of the RVR code to the BOLT command and control system. As the RVR utilizes the Python “asyncio” library to send asynchronous instructions through UART while the BOLT’s use a simple observer based Bluetooth command library, the BOLT functionality of the Agent class ultimately was unsuccessful. : [insert the results here and perform some analysis] comment -> results will show some swarming however will have required a maximum speed rule

## Collective Motion in Simulation

To understand the impacts of heterogeneity on swarming, simulations were run to identify possible challenges that may arise as well as to provide the groundwork for the future implementation of emergent collective motion. This was implemented using the CopelliaSim software, by implementing both species of robots as different scaled versions of the same robot. The simulations showed the following problems occurring:

* **Unexpected Collisions between Species:** Agents within the simulation suffered from a series of unexpected collisions, which resulted in agents having their swarm interactions disrupted, this can be seen in the figure below (figure 4A):

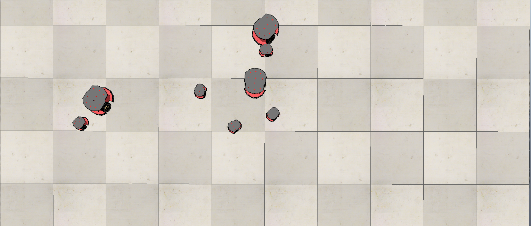
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Figure 4A: Simulation Unexpected Collisions

* **Swarm Divergence:** Swarm divergence occurred after initial convergence of the swarm, with agents becoming separated and moving out of the cohesion and alignment radii of their neighbours. This can be observed within the figure below (figure 4B):g

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Figure 4A: Simulation Unexpected Collisions

The findings from the simulations showed that the challenges that will need to be overcome within the research project during the implementation of the heterogeneous swarm, these are:

* **Velocity Scaling:** as the maximum velocity of the robots within the simulation were different, this resulted in agents requiring to move faster towards the swarm then their individual maximum velocity allowed, thus resulting in the separation seen within the simulations.
* **Boid Parameter Scaling:** as all agents within the simulation above used the same parameters, this resulted in issues with either species moving and reacting too quickly or too slowly; resulting in collisions and divergence. To overcome this challenge the Boid parameters will need to be scaled, so that the different species move differently with regard to their size and maximum and minimum velocities.

# Future Work

## Further Development, Testing and Validation

## Implement Emergent Collective Motion

The simulation has shown promise in the implementation of the current method, with functioning heterogeneous swarming working, the reinforcement learning model can be applied directly to the ‘Boid\_rules.py’ file and can hence achieve the desired collective motion that is the capitulation of this research project.

## Extension: Asymmetric Behaviour

Heterogeneous swarms are comprised of multiple different types of robots, the benefit of this is that swarming can draw upon different types robots and their respective strengths to create a cohesive swarm that exploits the strengths of each agent. In this case, a key strength of the BOLT is its simplicity and disposability in a high risk scenario. To model the conceptual idea the Boid swarm will implement a rule within formations to place BOLTs in lead positions as ‘scouts’ in front of the RVR, due to the RVR having a slower top speed but being more capable in realms of communications and sensing due to the Raspberry Pi.

# Conclusion

Objective

Summarise the research proposal

Summarise work done and future work

Value of research, including responding to the gap in literature

# References:

[1] M. Brambilla, E. Ferrante, M. Birattari, and M. Dorigo, “Swarm robotics: a review from the swarm engineering perspective,” *Swarm Intell*, vol. 7, no. 1, pp. 1–41, Mar. 2013, doi: 10.1007/s11721-012-0075-2.

[2] C. W. Reynolds, “Flocks, herds and schools: A distributed behavioral model,” in *Proceedings of the 14th annual conference on Computer graphics and interactive techniques*, in SIGGRAPH ’87. New York, NY, USA: Association for Computing Machinery, Aug. 1987, pp. 25–34. doi: 10.1145/37401.37406.

[3] A. E. Turgut, H. Çelikkanat, F. Gökçe, and E. Şahin, “Self-organized flocking in mobile robot swarms,” *Swarm Intell*, vol. 2, no. 2, pp. 97–120, Dec. 2008, doi: 10.1007/s11721-008-0016-2.

[4] R. B. Walton, F. W. Ciarallo, and L. E. Champagne, “A Unified Digital Twin Approach Incorporating Virtual, Physical, and Prescriptive Analytical Components to Support Adaptive Real-Time Decision-Making.” Rochester, NY, Jun. 28, 2023. doi: 10.2139/ssrn.4494073.

[5] V. R. Nagarajan and P. Singh, “Obstacle Detection and Avoidance For Mobile Robots Using Monocular Vision,” in *2021 8th International Conference on Smart Computing and Communications (ICSCC)*, Jul. 2021, pp. 275–279. doi: 10.1109/ICSCC51209.2021.9528162.

[6] R. Singh, A. Gehlot, A. Thakur, V. A. Shaik, and P. Das, “A Review on Implementation of Robotic Assistance in Covid-19 Epidemics: A Possibility Check,” vol. 29, pp. 7883–7893, Jul. 2020.

[7] G. Dietz, J. King Chen, J. Beason, M. Tarrow, A. Hilliard, and R. B. Shapiro, “ARtonomous: Introducing Middle School Students to Reinforcement Learning Through Virtual Robotics,” in *Proceedings of the 21st Annual ACM Interaction Design and Children Conference*, in IDC ’22. New York, NY, USA: Association for Computing Machinery, Jun. 2022, pp. 430–441. doi: 10.1145/3501712.3529736.

[8] F. Ducatelle, G. A. Di Caro, and L. M. Gambardella, “Cooperative self-organization in a heterogeneous swarm robotic system,” in *Proceedings of the 12th annual conference on Genetic and evolutionary computation*, Portland Oregon USA: ACM, Jul. 2010, pp. 87–94. doi: 10.1145/1830483.1830501.

[9] T. Balch and R. C. Arkin, “Behavior-based formation control for multirobot teams,” *IEEE Transactions on Robotics and Automation*, vol. 14, no. 6, pp. 926–939, Dec. 1998, doi: 10.1109/70.736776.

[10] S. Wan, J. Lu, and P. Fan, “Semi-centralized control for multi robot formation,” in *2017 2nd International Conference on Robotics and Automation Engineering (ICRAE)*, Dec. 2017, pp. 31–36. doi: 10.1109/ICRAE.2017.8291348.

[11] T. Balch and M. Hybinette, “Social potentials for scalable multi-robot formations,” in *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065)*, Apr. 2000, pp. 73–80 vol.1. doi: 10.1109/ROBOT.2000.844042.

[12] L. Barnes, M. Fields, and K. Valavanis, “Unmanned ground vehicle swarm formation control using potential fields,” in *2007 Mediterranean Conference on Control & Automation*, Jun. 2007, pp. 1–8. doi: 10.1109/MED.2007.4433724.

[13] D. Kengyel, H. Hamann, P. Zahadat, G. Radspieler, F. Wotawa, and T. Schmickl, “Potential of Heterogeneity in Collective Behaviors: A Case Study on Heterogeneous Swarms,” in *PRIMA 2015: Principles and Practice of Multi-Agent Systems*, Q. Chen, P. Torroni, S. Villata, J. Hsu, and A. Omicini, Eds., Cham: Springer International Publishing, 2015, pp. 201–217. doi: 10.1007/978-3-319-25524-8\_13.

[14] “Learning Decentralized Control Policies for Multi-Robot Formation | IEEE Conference Publication | IEEE Xplore.” Accessed: May 09, 2024. [Online]. Available: https://ieeexplore.ieee.org/document/8868898

[15] D. H. Stolfi and G. Danoy, “Optimising autonomous robot swarm parameters for stable formation design,” in *Proceedings of the Genetic and Evolutionary Computation Conference*, in GECCO ’22. New York, NY, USA: Association for Computing Machinery, Jul. 2022, pp. 1281–1289. doi: 10.1145/3512290.3528709.

[16] M. Hüttenrauch, A. Šošić, and G. Neumann, “Deep Reinforcement Learning for Swarm Systems,” *Journal of Machine Learning Research*, vol. 20, no. 54, pp. 1–31, 2019.

[17] M. B. Bezcioglu, B. Lennox, and F. Arvin, “Self-Organised Swarm Flocking with Deep Reinforcement Learning,” in *2021 7th International Conference on Automation, Robotics and Applications (ICARA)*, Feb. 2021, pp. 226–230. doi: 10.1109/ICARA51699.2021.9376509.

[18] M. Egerstedt and X. Hu, “Formation constrained multi-agent control,” *IEEE Transactions on Robotics and Automation*, vol. 17, no. 6, pp. 947–951, Dec. 2001, doi: 10.1109/70.976029.

[19] M. M. Khan, K. Kasmarik, and M. Barlow, “Autonomous detection of collective behaviours in swarms,” *Swarm and Evolutionary Computation*, vol. 57, p. 100715, Sep. 2020, doi: 10.1016/j.swevo.2020.100715.

[20] S. Abpeikar, K. Kasmarik, M. Garratt, R. Hunjet, M. M. Khan, and H. Qiu, “Automatic collective motion tuning using actor-critic deep reinforcement learning,” *Swarm and Evolutionary Computation*, vol. 72, p. 101085, Jul. 2022, doi: 10.1016/j.swevo.2022.101085.

[21] G. Di Marzo Serugendo *et al.*, “Self-Organisation: Paradigms and Applications,” in *Engineering Self-Organising Systems*, G. Di Marzo Serugendo, A. Karageorgos, O. F. Rana, and F. Zambonelli, Eds., Berlin, Heidelberg: Springer, 2004, pp. 1–19. doi: 10.1007/978-3-540-24701-2\_1.

[22] “Collective Robotics: From Social Insects to Robots - C. Ronald Kube, Hong Zhang, 1993.” Accessed: May 10, 2024. [Online]. Available: https://journals.sagepub.com/doi/abs/10.1177/105971239300200204?casa\_token=eQiuPn8kxvsAAAAA:sKx3Wnfr7IqWSHhYv-K-E8vqr9vAV7HWCFol\_wgqzZqRW9HkKU2fgazOrGMgJIXsNZn9CRYMc7Q

[23] Z. Xiaoning, “Analysis of military application of UAV swarm technology,” in *2020 3rd International Conference on Unmanned Systems (ICUS)*, Nov. 2020, pp. 1200–1204. doi: 10.1109/ICUS50048.2020.9274974.

[24] W. Du *et al.*, “Network-Based Heterogeneous Particle Swarm Optimization and Its Application in UAV Communication Coverage,” *IEEE Transactions on Emerging Topics in Computational Intelligence*, vol. 4, no. 3, pp. 312–323, Jun. 2020, doi: 10.1109/TETCI.2019.2899604.

[25] A. Liekna and J. Grundspenkis, “TOWARDS PRACTICAL APPLICATION OF SWARM ROBOTICS: OVERVIEW OF SWARM TASKS,” *ENGINEERING FOR RURAL DEVELOPMENT*.

[26] M. Schranz, M. Umlauft, M. Sende, and W. Elmenreich, “Swarm Robotic Behaviors and Current Applications,” *Front. Robot. AI*, vol. 7, Apr. 2020, doi: 10.3389/frobt.2020.00036.

[27] E. Şahin, “Swarm Robotics: From Sources of Inspiration to Domains of Application,” in *Swarm Robotics*, E. Şahin and W. M. Spears, Eds., Berlin, Heidelberg: Springer, 2005, pp. 10–20. doi: 10.1007/978-3-540-30552-1\_2.

[28] R. Sawant, C. Singh, A. Shaikh, A. Aggarwal, P. Shahane, and H. R, “Mine Detection using a Swarm of Robots,” in *2022 International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI)*, Chennai, India: IEEE, Jan. 2022, pp. 1–9. doi: 10.1109/ACCAI53970.2022.9752481.

[29] M. Dorigo, G. Theraulaz, and V. Trianni, “Reflections on the future of swarm robotics,” *Science Robotics*, vol. 5, no. 49, p. eabe4385, Dec. 2020, doi: 10.1126/scirobotics.abe4385.

[30] M. Dorigo *et al.*, “Swarmanoid: A Novel Concept for the Study of Heterogeneous Robotic Swarms,” *IEEE Robotics & Automation Magazine*, vol. 20, no. 4, pp. 60–71, Dec. 2013, doi: 10.1109/MRA.2013.2252996.

[31] F.-J. Mañas-Álvarez, M. Guinaldo, R. Dormido, R. Socas, and S. Dormido, “Formation by Consensus in Heterogeneous Robotic Swarms with Twins-in-the-Loop,” in *ROBOT2022: Fifth Iberian Robotics Conference*, D. Tardioli, V. Matellán, G. Heredia, M. F. Silva, and L. Marques, Eds., Cham: Springer International Publishing, 2023, pp. 435–447. doi: 10.1007/978-3-031-21065-5\_36.

[32] M. Nakamura, “Dynamic patterns formed by heterogeneous boid model composed of agent groups moving reversely,” *Artif Life Robotics*, vol. 27, no. 2, pp. 373–383, May 2022, doi: 10.1007/s10015-022-00743-0.

[33] A. Prorok, M. A. Hsieh, and V. Kumar, “The Impact of Diversity on Optimal Control Policies for Heterogeneous Robot Swarms,” *IEEE Transactions on Robotics*, vol. 33, no. 2, pp. 346–358, Apr. 2017, doi: 10.1109/TRO.2016.2631593.

[34] H. Van Dyke Parunak and S. A. Brueckner, “Engineering Swarming Systems,” in *Methodologies and Software Engineering for Agent Systems: The Agent-Oriented Software Engineering Handbook*, F. Bergenti, M.-P. Gleizes, and F. Zambonelli, Eds., Boston, MA: Springer US, 2004, pp. 341–376. doi: 10.1007/1-4020-8058-1\_21.

[35] M. Dorigo, G. Theraulaz, and V. Trianni, “Swarm Robotics: Past, Present, and Future [Point of View],” *Proceedings of the IEEE*, vol. 109, no. 7, pp. 1152–1165, Jul. 2021, doi: 10.1109/JPROC.2021.3072740.

[36] C. Pinciroli, R. O’Grady, A. L. Christensen, and M. Dorigo, “Coordinating Heterogeneous Swarms through Minimal Communication among Homogeneous Sub-swarms,” in *Swarm Intelligence*, M. Dorigo, M. Birattari, G. A. Di Caro, R. Doursat, A. P. Engelbrecht, D. Floreano, L. M. Gambardella, R. Groß, E. Şahin, H. Sayama, and T. Stützle, Eds., Berlin, Heidelberg: Springer, 2010, pp. 558–559. doi: 10.1007/978-3-642-15461-4\_59.

[37] K. Kasmarik, S. Abpeikar, M. M. Khan, N. Khattab, M. Barlow, and M. Garratt, “Autonomous Recognition of Collective Behaviour in Robot Swarms,” in *AI 2020: Advances in Artificial Intelligence*, M. Gallagher, N. Moustafa, and E. Lakshika, Eds., Cham: Springer International Publishing, 2020, pp. 281–293. doi: 10.1007/978-3-030-64984-5\_22.

[38] “Sphero BOLT.” Accessed: May 12, 2024. [Online]. Available: https://support.sphero.com/en-US/articles/bolt-72242

[39] “Sphero Edu API — SpheroV2 0.12 documentation.” Accessed: May 12, 2024. [Online]. Available: https://spherov2.readthedocs.io/en/latest/sphero\_edu.html

[40] “Sphero Public SDK - Documentation.” Accessed: May 12, 2024. [Online]. Available: https://sdk.sphero.com/documentation

[41] “Vicon Help.” Accessed: May 13, 2024. [Online]. Available: https://help.vicon.com/

[42] “Raspberry Pi Documentation.” Accessed: May 13, 2024. [Online]. Available: https://www.raspberrypi.com/documentation/

[43] “bleak — bleak 0.22.1 documentation.” Accessed: May 13, 2024. [Online]. Available: https://bleak.readthedocs.io/en/latest/