Heterogenous Swarm of RVR and BOLT Robots:

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Abstract - Swarming intelligence in nature is a testament to the rigorous evolutionary ecosystem, it demonstrates how multiple agents with limited abilities can form large cooperative swarms that develop emergent collective behaviours. Swarm robotics is the study of artificial robotic swarms akin to their biological counterparts, the Boid swarming model is an artificial implementation of natural swarm intelligence, inspired by the flocking nature of birds, characterised by clearly defined rules which govern the actions of agents by the actions of their neighbouring agents and vice versa. While the field of swarm robotics is pervaded by research with homogeneous swarms, heterogeneous swarms have shown clear benefits over homogeneous swarms due to the use of multiple different species of robots, widely expanding the capability and mobility of swarms. Through heterogeneity swarms can begin to approach increasingly novel challenges and prove to be crucial systems with both widespread and niche applications in a variety of environments. Within natural swarms, a common developed emergent behaviour is that of collective motion in a given formation; ants move in lines to improve efficiency of transport and birds move in v – shapes to reduce aerodynamic drag, artificial robotic swarms can too be optimised through formations. This research project seeks to implement emergent collective motion within a Boid swarm – based model within a heterogeneous swarm utilising Sphero BOLT and RVR robots in a novel approach in the formation of heterogeneous swarms.

Contents:

I. Introduction

II. Background Information

A. Boid Swarming Algorithm

The boids model was first conceptualised and implemented by Craig Reynolds [4] in 1986, which simulated the flocking motions of birds for computer graphics using three rules: separation, cohesion and alignment, that governed how individual agents moved with reference to those around them without a centralised control system. The Boid swarming algorithm utilised within this paper is described algebraically by Khan et al. [5] where at timestep t for N agents $\{A^1, A^2, \dots, A^N\}$, an individual agent A^i calculates three distinct vectors for each force of separation, cohesion and alignment through it's own and it's neighbour's position x_t^i and velocity v_t^i, where neighbours are defined as any agent A^k where the distance does not exceed that rule's radius R (rules may have different radii, resulting in different patterns and behaviours). Formally this is given by set $\boldsymbol{N}^i$:

$$\boldsymbol{N}^i = \{A^k \neq A^i \wedge dist\,(A^k, A^i) < R\}$$

Where $dist(A^k, A^i)$ represents the Euclidean distance between two agents. Thus, to calculate each rule the average position of agents within the rule's radius is calculated. For cohesion, the agent A^i will take the average position $\overline{\boldsymbol{c}}_t^i$ of N_c agents A^k within range R_c:

$$\overline{\boldsymbol{c}}_t^i = \frac{\sum_k x_t^k}{\left|(N_c)_t^i\right|}$$

Thus, the cohesion vector $\boldsymbol{c}_t^i$ is calculated as a vector from the agent A^i towards $\overline{\boldsymbol{c}}_t^i$:

$$\boldsymbol{c}_t^i = \overline{\boldsymbol{c}}_t^i - x_t^i$$

Similarly, for the separation vector $\boldsymbol{s}_t^i$, where the vector is calculated as a vector away from the average position of neighbours $\overline{\boldsymbol{s}}_t^i$ within range R_s:

$$\overline{\boldsymbol{s}}_t^i = \frac{\sum_k x_t^k}{\left|(N_s)_t^i\right|}$$

$$\boldsymbol{s}_t^i = x_t^i - \overline{\boldsymbol{s}}_t^i$$

For the alignment vector $\boldsymbol{a}_t^i$, where the vector is given as the average heading of agents within range R_a, thus:

$$\overline{\boldsymbol{a}}_t^i = \frac{\sum_k v_t^k}{\left|(N_a)_t^i\right|}$$

These vectors are subsequently combined each timestep to update the velocity and heading of the agent A^i:

$$v_{t+1}^i = v_t^i + W_c \boldsymbol{c}_t^i + W_a \boldsymbol{a}_t^i + W_s \boldsymbol{s}_t^i$$

The implementation of the Boid algorithm is a key progression in the field of swarm robotics, allowing different processes to both analyse and understand as well as to manipulate each of the swarm parameters to emulate nature.

B. Emergent Collective Motion

Natural swarm intelligence forms the fundamental basis for the research of swarm robotics, in nature geometric formations of swarms often develop from basic agents which do not have higher level control. While research into formation control focuses on the control of swarms through the implement of various different control methods to force the robotic swarm into the emulation of a natural swarm, there is a growing field of research into both the cultivation and observation of emergent behaviour [6], [7], where swarms form own collective motions developed from basic rules. The scope of this research project heavily focuses on the emergent collective motion that occurs within Boid swarms through modification to the Boid swarm parameters, Khan et al. [5] devised a method for the autonomous detection of collective motion while Abpeikar et al. [8], [9] utilised deep reinforcement learning to create sets of parameters that produce certain formations as well as a transfer learning solution to implement these formations within the Boid parameters of Sphero BOLT swarms. This research project aims to extend these concepts and apply them into a heterogeneous swarm.

III. Literature Review

A. 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 behaviours 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 [4] 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 centre of the flock. By implementing these three rules Reynolds created a simulation that modelled the flocking of birds. While Reynolds' work in 1987 was centred 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 [10]. 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.

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 [11], [12], practical [13] and educational opportunities [14]. Emergent behaviours 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 [15], [16], [17], 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 [18], [19], [20]. 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 [21], [22]. 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 [21], [22], 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. [23], who controlled the entire swarm through the use of deep reinforcement learning, Bezcioglu et al. [24] demonstrates flocking through a global state space matrix utilizing deep reinforcement learning, Egerstedt and Hu [25] 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. [5] 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. [8] 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. [8] and to reproduce this within heterogeneous swarms.

B. Applications of Heterogeneous Swarms

Throughout nature both homogeneous and heterogeneous swarms develop to solve distinct and unique problems [26], [27], 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 [13], [28], [29], [30], [31], [32]. 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 [32]. Both physical and behavioural heterogeneity within swarms opens up new dimensions in terms of capabilities and possibilities for swarm intelligence [33]. While hallmark papers such as Swarmanoid [34] 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.

As research into swarm robotics has developed, swarm robotics have begun to be conceptualized, simulated and implemented into real world challenges in comparison to lab – based conceptual problems. For example, robotics swarms are 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 [35], 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. Furthermore, heterogeneous robotic swarms have seen the most real and proposed application within difficult terrain based systems, explicitly those with innate communications interference and denial, as de – centralized, robust scalable heterogeneous swarms significantly appear as solutions to these problems [36]. This has been seen in subterranean exploration in the research project by Hudson et al. [3] where, as previously discussed, heterogeneous swarms successfully path planned and mapped in a subterranean complex, as discussed within the introduction. Further applications include those within the underwater environment, where operations within the sub – surface space are pervaded by the denial of long – range communications and sensing, Shkurti et al. [37] implemented a heterogeneous system of different agents to conduct multi – domain monitoring of marine environments. Heterogeneous swarming is a natural progression of developments within diverse multi – robot systems, providing flexibility, robustness and scalability through their very nature. Thus, the applications of heterogeneity are dominated by the varying viability of different physical and behavioural natures of a broad range of autonomous agents.

Recent research has shown success in formations and collective motion of heterogeneous swarms with differing levels of diversity within the swarm populations [38], [39], [40]. 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 [8], 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.

C. Benefits of Heterogeneous Swarms and Collective Motion

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 [41]. 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 [42]. An approach to the widely opened horizons of heterogeneous swarming can be seen within the experiment by Dorigo et al. [34], 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 [43], 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 [40]. Hence a monumental benefit of heterogeneous swarms over their classical counterparts is their ability to optimize the efficiencies and capabilities of different species of robots to achieve complex tasks typically reserved for non – swarm based single and multi – agent systems.

Collective motion within swarms can provide both crucial positioning to optimize efficiency as well as

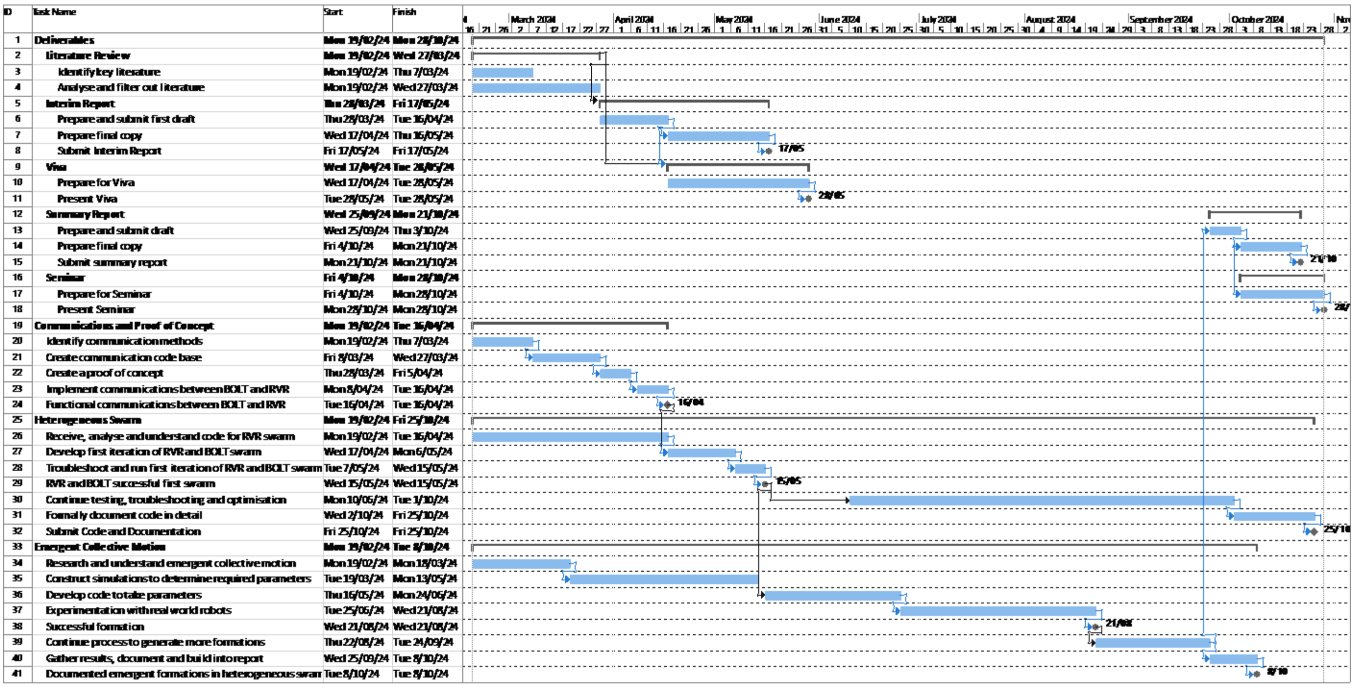

Figure 1: Gantt Chart for the Research Project

organization and redundancy within swarms, this is particularly imperative to heterogeneous swarming due to the different capabilities and behaviours possibly presented by different species. Inacio et al. [44] used particle swarm optimization to demonstrate a control method for the segregation of different species of swarms, while [15] demonstrates the innate emergent collective motion of robots within a heterogeneous system, utilizing Swarmanoid [34] type 'eye', 'foot' and 'hand' robots to simulate different attraction and repulsion reactions within a foraging task. Additionally, Kengyel et al. [20] conceptualizes heterogeneous swarms moving in heterogeneous behaviours modelled on honeybees, these show the viability of the optimization and implementation of collective motion within heterogeneous swarms to developing faster, more efficient heterogeneous swarms. While emergent collective behaviour, particularly collective motion bears a resemblance to formation control methods mentioned above, emergent collective behaviour differs through the methodology of controlling and developing certain formations. Abpeikar et al. [9] utilizes transfer learning from simulations to directly modify Boid parameters for formations to emerge within the swarm this is different to research mentioned above, where formations typically utilise a strict graphical means, or where they are otherwise implemented in a rule – type way. Thus collective motion provides a large benefit to the efficiency and redundancy of heterogeneous swarms with emergent collective motion maintaining scalability and flexibility if the swarm is changed or is influenced by an outside force.

IV. Planning

A. 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 Figure 1.

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 28 Oct 2024, which entails the submission of python code package, documentation as well as a summary report (25 Oct 2024), by aiming to complete first draft of the summary report by 03 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.

B. 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:

1) 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.

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

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

4) 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.

V. Methodology

A. 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.

B. 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 [4].

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

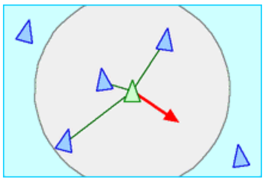

Figure 2A: Separation Diagram [4]

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

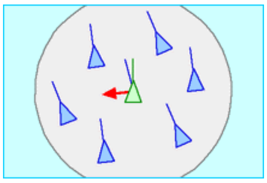

Figure 2B: Alignment Diagram [4]

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

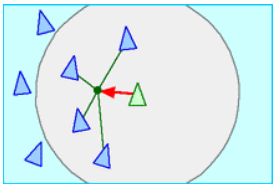

Figure 2C: Alignment Diagram [4]

Figures above are exactly reused and made by Craig Reynolds [4]. Each fundamental swarming force has additional Boid and situational awareness parameters [5], [45], these are:

- **W_s, W_a, W_x:** Weights for separation, alignment, and cohesion

- **V_{max}, V_{min}:** Maximum and minimum velocity

- **R_s, R_c, R_a:** Separation radius, cohesion radius, and alignment radius

By modifying these parameters it is possible to create emergent behaviours resulting in collective motion and formations, shown by Khan et al. and Abpeikar et al. [5], [8], as discussed within the literature review. Some of these formations include, line behaviour, which emulates the orderly movement of ants within a line formation and flocking behaviour, which emulates the V – shaped formation that birds form when travelling long distances, figure 3 depicts these behaviours within the context of modifying the Boid parameters to generate formations , the figure is exactly reused from the paper by Khan et al. [5]. This methodology to achieving emergent collective motion within Boid swarms shows promise with adaptation to heterogeneity, to implement this within a heterogeneous swarm further simulations will be completed with trials in both species specific and agnostic parameter sets.

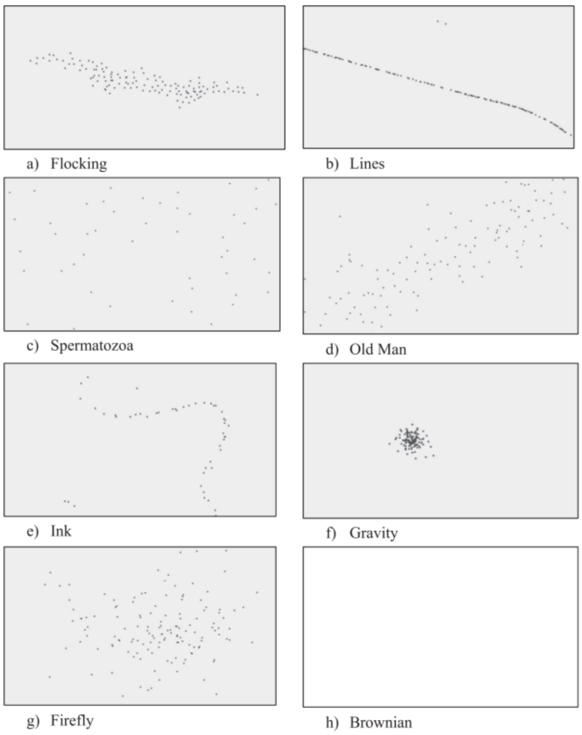

Figure 3: Emergent Collective Motion [5], each motion has its own set of unique parameters that cause the formation to emerge

VI. Current Progress

C. 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 [46], [47], [48].

Figure 4A (left) and Figure 4B (right): Sphero BOLT (left) and RVR (right)

The BOLT (figure 4A) 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 [46].

The other agent utilised in the heterogeneous swarm is the Sphero RVR (figure 4B) 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 [48].

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 [49].

While both robots are produced by Sphero, utilizing many identical control schemes, sensors, firmware and APIs [46], [47], [48], 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 [50]. 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 to successfully complete the research project such as the design of the overall system architecture diagram (figure 6) as well as the final structures for the implementation of emergent collective motion.

D. 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 [46], [47], [51].

- **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 [46], [47].

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 together, this can be observed in Figure 5. The communications test showed both BOLT and RVR initializing and moving together successfully through Bluetooth within the Raspberry Pi as well as the Vicon system successfully tracking the data of each robot.

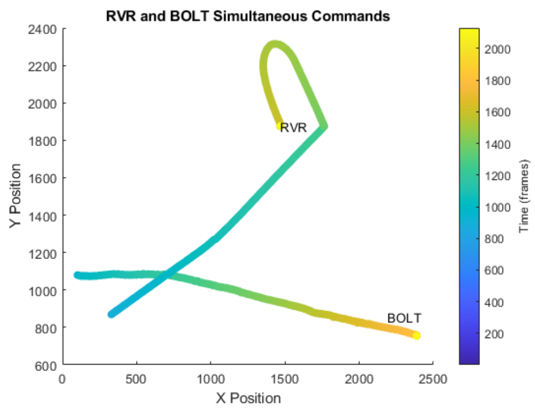

Figure 5: Communications Test Positions, time represented by colours of path changing, X and Y positions are from Vicon

E. 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 6 below is the system architecture diagram which shows the conceptualization of how the total code will work. 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

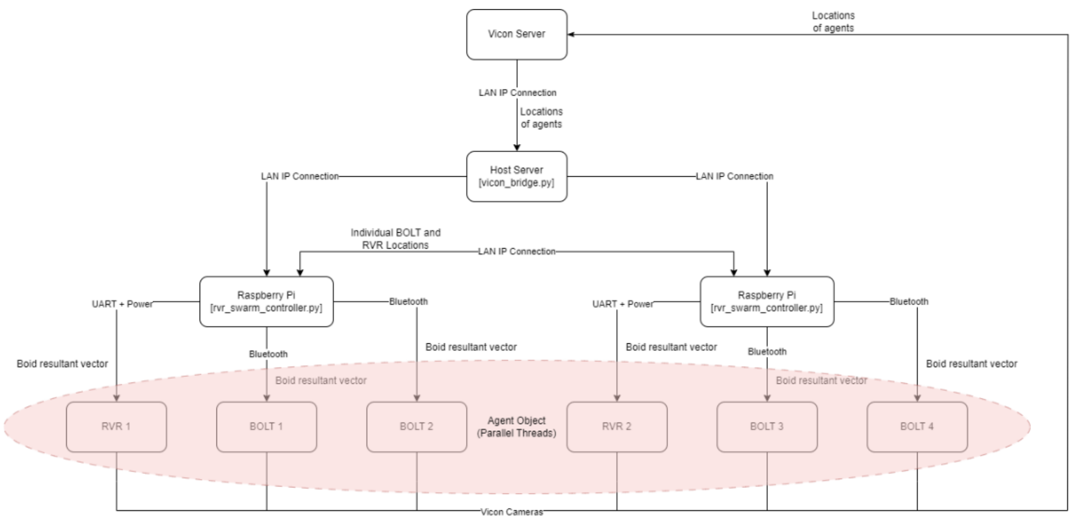

Figure 6: System Architecture Diagram, showing data flow of swarm

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, this resulted in the SpheroV2 library unable to move the BOLT under asynchronous control, this resulted in a redevelopment of the code with significant changes and increased modularity through the use of an RVR and BOLT specific class as well as an independent Vicon handler class that runs in parallel on the Raspberry Pi. This version of the code may encounter problems with the computational power and speed of the Raspberry Pi.

F. Identifying the Challenges of Heterogenous Collective Motion using CoppeliaSim.

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 7A):

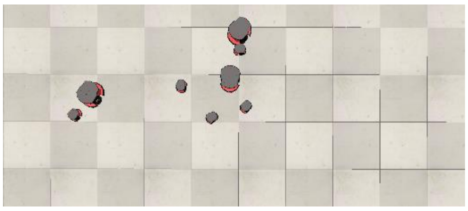

Figure 7A: Simulation Unexpected Collisions

- **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 7B):

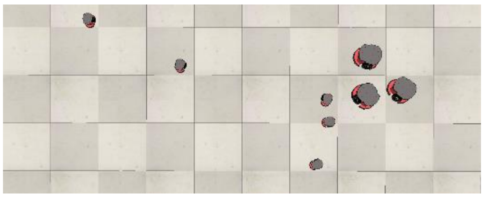

Figure 7B: Simulation Swarm Divergence

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 moving 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.

VII. Future Work

A. Further Development of Swarm Code

As the full heterogeneous swarming code is not currently functioning this will require further development. As the development of the code continues further testing and refinement of the code will be required, this will include optimizing the code for speed and efficiency. To further improve the code testing and validation will be required,
this will be achieved through the use of data logging to determine if the swarms are correctly moving within the Boid swarming parameters and that the swarm is being formed. There may also be additional challenges created from the RVR and BOLT's respective differences in motor power and size.

B. 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 end state of this research project. In order to effectively achieve this, further simulations and the possibility of transfer learning to develop the parameters required to generate parameters so that collective motion emerges from the swarm. Additionally, further work may include species specific Boid parameters to model certain natural heterogeneous swarm intelligence.

C. 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 of 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 and demonstrate these different formations, experiments will be conducted to change Boid parameters, or to implement additional rules for interactions between agents.

VIII. Conclusion

The overall objective of this research project is to create a heterogeneous swarm utilising Sphero BOLT and RVR robots and to, within this swarm implement the work of Khan et al. [5] and Abpeikar et al. [8] to develop the parameters required to create emergent collective motion and to then implement these formations within the heterogeneous swarm through modification of the parameters of the Boid swarm rules. This represents a novel combination of multiple different research works that seeks to emulate natural phenomena found in swarms, where natural swarms form collective motion such as formations through de – centralized interactions between agents.

The current progress towards the final deliverable product has been to initially establish communications between the RVR and BOLTs, providing results to show that RVR and BOLTs can be controlled simultaneously utilising the Raspberry Pi that resides onboard the RVR, as well as to develop a code base on which to instantiate the RVR and BOLTs as individual Boid agents so that they can effectively act as Boid swarm agents and form a heterogeneous Boid swarm by both transmitting and receiving their own respective positional data to accurately calculate their own movements within the entire swarm. While current progress has been unable to initiate the entire swarm there has been great progress towards the development of a final code that will be able to handle a scalable swarm of both RVRs and BOLTs. Additionally, progress has been made in the development of a simulation package that models a heterogeneous swarm that will act as an analogue to the RVRs and BOLTs with a larger robot that moves at a slower maximum velocity to the smaller and faster BOLTs. Hence, while current progress is tracking slightly behind schedule, issues found within the heterogeneous swarming code have been identified and reworked and should be functional after further troubleshooting, while the pre – existing communications code and simulation package will provide a baseline to inform the second phase of development within this research project.

This project will continue to further investigate and improve upon the development and implementation of formations as a result of emergent collective motion within a heterogeneous swarm. In order to achieve this, the knowledge gained from both simulation and development of the heterogeneous swarming code will inform on the possible challenges with the future development of the final code build, which will incorporate both the heterogeneous swarming code developed to date while incorporating emergent collective behaviours. With scope within this research project to further extend the project to develop and incorporate emergent collective behaviour in an asymmetric fashion within the swarm, this will provide further real-world context to the heterogeneous swarm and aim to exploit the strengths and weakness of each species within the swarm.

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