Hybridization of the minimal Environment Driven Evolutionary Algorithm with a multi-Behavior Characterization Map-Elites Algorithm

Literature Review

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ABSTRACT

Functional diversity within groups of animals in the real-world has shown to create species that can perform a wider variety of tasks better, allowing for the groups to perform efficiently and ensure a level of adaptability that allows them to overcome new challenges. As such, this is a natural phenomenon that we should endeavor to mimic in evolutionary algorithms in swarm-robotics, creating collections of robots that have quality diversity rather than being specialized in a singular task. In order to carry this out, an evolutionary algorithm needs to be created, that can allow for the new generations of robots to be created that can perform different tasks better than their predecessors, while also maintaining enough characteristic diversity that they do not become too uniform. In order to build this algorithm initially, we will use an evolutionary algorithm called the minimal environment driven evolutionary algorithm (mEDEA) hybridized with a multi-behavior characteristic (multi-BC) multi-dimensional archive of phenotypic elites (MAP-elites), to allow for diversity in during robot phenotype generation.

CCS CONCEPTS

• Computing methodologies

KEYWORDS

Evolutionary robotics, Evolutionary algorithms, MAP-Elites, Swarm robotics, Adaptive robotics

ACM Reference format:

Kevaalin Rapeti, 2022. Hybridization of the minimal environment driven evolutionary algorithm with a multi-behavior characterization map-elites algorithm: Literature Review Here. In *Proceedings of ACM Woodstock conference (WOODSTOCK'18). ACM, New York, NY, USA, 2 pages.* https://doi.org/10.1145/1234567890

1 Introduction

In nature there exists multitudes of different species, which have developed to survive using a group dynamic. This can be seen very prominently in the insect world as well as in human society, such that sub-groups of individuals learn and specialize at completing certain tasks in order for the group to become more adaptable to changing environments as described by Hamann and Schmickl (2012) [1]. Focusing on this concept in insects and creating a parallel to the world of robotics, we are able to describe the idea of swarm robotics. As described by Brambill, et al (2013) [2] swarm robotics is an approach to collective robotics that takes inspiration from the self-organized behaviours of social animals.

The benefits of using swarm robotics are based on their ability to specialize for functional diversity, allowing the swarm to accomplish more diverse tasks, making them more effective in unknown environments. As stated by Spezzano (2019) [3], one of the objectives of swarm robotics, is to create a group of organisms, where the group exhibits group behavior which allows for it to complete tasks collectively which would be impossible to accomplish for any of its individual members. This swarm can even be heterogenous instead of just homogenous, allowing for the swarm itself to have a higher level of complexity as described by Hamann (2018) [4], but with a higher level of complexity comes the challenge of proper functionality of the swarm to achieve its goals. A balance between complexity of the robot swarm and reliability of its functionality needs to be established, so that we as the researcher are able to generate a robotic swarm that is properly designed for the tasks we have in our experiments.

In order to achieve this level of functional diversity and swarm complexity we will need to use evolutionary algorithms, to generate new swarms based on data from previous generations, allowing us to eventually create a generation that is better fitted to the environment and the objectives found in it.

An important aspect of swarm robotics is swarm intelligence which as stated by Kennedy (2006) [5] can be described as the problem-solving ability derived from the interactions of simple information-processing units but is also described by Dorigo and Birattari (2007) [6] as the discipline that deals with natural and artificial systems composed of many individuals that coordinate using decentralized control and self-organization. Based on these two definitions we can see that the key aspects of swarm intelligence depend on the interactivity held between robots in the swarm, done by interactions between individuals which can range from simple to complex. Such as communication about the environment between robots, validation of an entity in the swarm of message passing.

We will also need to design and implement optimization algorithms for the swarm, so that the swarm intelligence of future generations of the swarm is more functional, efficient and better adapted to its environment than that of previous generations. To do this we can refer to the impact of swarm intelligence-based optimization algorithms from the work done by Yang, et al, (2013) [7] and the impact of swarm intelligence-based optimization algorithms and self-organization which is examined by Yang, et al (2018) [8]. From this we can determine how best to handle swarm intelligence optimization algorithms in order to ensure that as we generate new generations of the swarm we will be able to converge on collective behaviours which will be best suited for their environment.

This proper handling of swarm intelligence is what can help us to design the behavioural characteristics of the individual robots as well as the swarm. This design characteristic for the overall swarm can also be called their collective behaviour, in the past there has been collective behaviours designed to handle already know environments where there was isolated reproduction of each new generation as described by Hart, Steyven and Paechter (2018) [9]. This helped create a generation of robots suited to the environment, however, required too much external influence and is not suitable to implement in real-world scenarios where such influence may not be possible. So we look then to our evolutionary algorithm, namely a hybridized version of the minimal environment driven evolution algorithm (mEDEA) and the multi-behaviour characterization (multi-BC) Map-Elites algorithms. In order to let the robots, become an efficient and adaptive swarm.

In the attempt to create this efficient and adaptive swarm, we will need to look into adaptive collective behaviour (ACB) to see how it can positively influence the functionality of a robotic swarm along with its quality diversity. ACB has been exhibited in the natural world many times, found in swarm animals and insects alike as described by Feng, Gribaudo and Hillston (2015) [10]. They also state that with regards to emergent behaviour of the swarm, these become easily apparent at a population level, but not so prevalent at an individual level. What we will need to take away from this fact, is that when designing how the swarm will act as an entity, the controller for individual robots will be designed with this in mind, and we will need to ensure that good controller design can allow for the emergent behaviour to appear at the population level.

2 Collective Behaviour Tasks

One of the key defining characteristics of a robotic swarm, is how it is able to handle collective behaviour tasks. This is what defines the difference between swarm robotics and individual robotics, since if we created the swarm such that a single individual of the swarm could complete all the tasks by itself, but that it would just take longer, then we are not really using swarm robotics to its full potential.

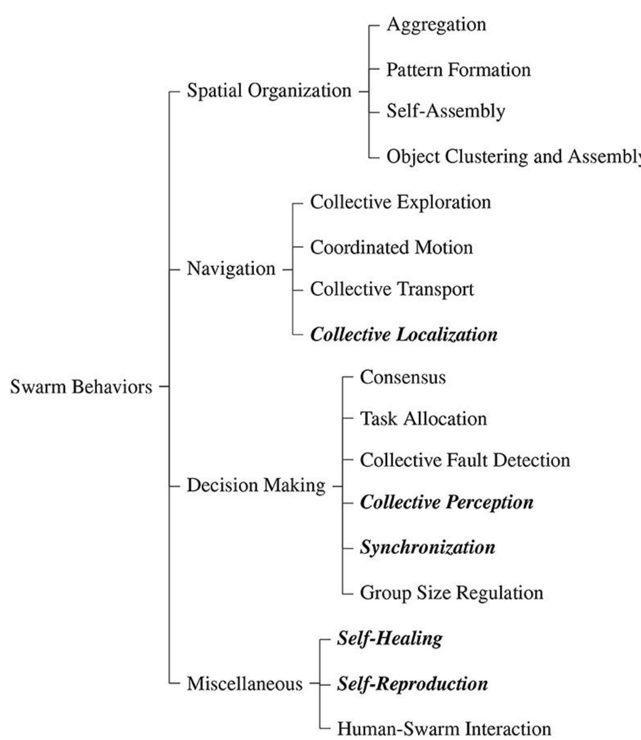

Figure 1: A list of swarm behaviours and their sub-categories. Schranz, et al (2020) [11]

First we shall describe some behaviours which are used in swarm robotics. These have been defined by Brambilla, et al (2013) [2], in which they have listed three key areas of collective behaviour: spatially-organizing behaviours, navigation behaviours and collective-decision making behaviours with the possibility of more being defined in the future. In Figure 1, we can see the original three categories defined by Brambilla, et al (2013) [2], with additions made by Schranz, et al (2020) [11] to include a category on miscellaneous behaviours which the swarm could exhibit.

Described in the paper by Schranz, et al (2020) [11], they look into what considerations should be looked at when considering a swarm's collective behaviours, and what we as the designer should treat as objectives for the swarm in order for it to properly adapt to its environment. Some of the objectives are listed in Figure 1 but depending on the specifics of the swarm and their task, some behaviours may be weighted higher than others.

In the process of designing good collective behaviour tasks, the starting point would be to first start off with defining and implementing a good basic swarm behaviour. These basic behaviours will be defined with a set of local rules which the individuals can interact with the environment with, and from this the overall collective behaviour will emerge in a more organic nature.

3 Swarm intelligence and Collective Behaviour

Before we look into how the swarm as a collective will behave, first we must take a look at the individual robot, in order to understand its abilities, constraints, strengths and weaknesses. In terms of design, each robot will comprise of a collection of sensors and motors. These sensors will be used by the robot in order to identify objects in its surroundings and the motors will be used in order for the robot to navigate the environment. From the paper on swarm robotic behaviours and current applications described by Schranz, et al (2020) [11].

From this paper we can get an idea of what kind of actions we should allow the individual robots to perform: they should be able to handle collective localization, to identify where they are in relation to other robots; they should be able to have collective perception, passing the data they collect each generation locally to other members of the swarm so they swarm can make more informed decisions; the ability to synchronize, allowing robots to understand what other robots are doing, and to help them if the need arises; and most importantly reproduction, wherein each robot is able to pass on their characteristics to future generations of the swarm, based on a criteria that will make future generations more effective in their environment.

In the first step to better understanding collective behaviour, first we shall look at a better definition of what it is. Based on the work by Reicher (1982) [12], we can define collective behaviour being the idea of a collection of individuals who carry out actions based on the information stored internally and received from other individuals in the collection, in order to carry out some pre-determined tasks. From this we can understand that the robots in the swarm have the ability to interpret information of their environment and interact with it on their, but most of their information should come from other robots in the environment. Looking at the paper on collective decision-making by Jiang, Cheng and Chen (2022) [13], we see that we should not treat all robots the same when it comes to the information they hold. Depending on where in the environment a robot is, the information they gather could be more or less relevant to the objectives of the swarm. Therefore, we would need to take into consideration the type of information a robot has and what it is passing on to others in the collection in order to make sure it is relevant to the swarm. This can help us to remove any "noise" from the data collected and help create a more effective new generation.

3.1 Methods for Adapting Collective Behavior

To help facilitate the generation of new robots we will be looking at the hybridization of two specific algorithms. The mEDEA and multi-BC Map-Elites algorithm to see if we can make a more effective evolutionary algorithm than if we were to use either in isolation.

3.1.1. Minimal Environment Driven Evolutionary Algorithm. In mEDEA, the objective of the algorithm is that each robot transfer its own "genome" of characteristics to other robots it comes across in the environment, each robot will interact with its environment based on its control algorithm and at the end of the generation's lifetime stop broadcasting as described by Hart, Steyven and Paechter (2018) [9]. This algorithm has strengths in sharing information across individuals in the swarm. Originally mEDEA would just pass on information about the specific robot to others, but this can and has been altered in experiments after the original paper.

mEDEA originally was derived from the Environment-driven Distributed Evolutionary Adaption (EDEA) algorithm, which focused on an extrinsic and intrinsic motivation for the algorithm to work. The extrinsic motivation, focused on the environmental constraints that the robot found itself in, and based on the requirement of the robot would determine the best characteristics for the robot to survive. The intrinsic motivation, focused on the "genomes" passed between robots in the simulation, so robots which came into contact with other more often were more likely to pass their "genome" as described by Bredeche and Montanier (2010) [14]. mEDEA was created with the idea of the EDEA algorithm, but instead focusing on a smaller local environment, hence, "minimal".

3.1.2 Multi-Behaviour Characterization Map-Elites. Map-elites is a quality diversity algorithm, a type of algorithm that focuses on creating a diverse collection of high-quality behaviours. Allowing the robots to create these high-quality behaviours in a single generation as described by Hart, Steyven and Paechter (2018) [9]. A further explanation of how the Map-Elites algorithm works, is that the user will choose a performance measure for the simulation, then the user creates an N-dimensional feature space which will determine the variations of interest for the user. Each of the dimensions found in the feature space is then given a valuation, in order to determine a priority ranking, and over each generation the algorithm checks for the highest performing "cell" in the feature space as described by Mouret and Clune (2015) [15].

3.2 Inhibiting Poor Quality Characteristics

In the construction of the collective behaviour of the robotic swarm, one risk we have to take into consideration it that of poor-quality data/behaviours or noisy data. This is can pose a high risk to the research project since if not handled as the simulations are run and monitored accordingly, we could generate a poorly designed robotic swarm. One of the ways we can get noisy data is based on the readings by our sensors on the robots. If they are not tested correctly or if we do not filter the information they receive properly we could suffer from noisy data which would inhibit the abilities of the swarm as described by Lee, Lawry and Winfield (2021) [16].

A different issue we can find is with regards to collective decision-making, in the paper by Masi, et al, (2021) [17] in designing the robots and their ability to communicate new and relevant information about the environment we need to ensure that we do not allow "stubborn" individuals to be created and this "stubborn" trait to be passed on to future generations. Here "stubborn" refers to individual robots in the swarm, which when they receive new information from other informed robots, they choose to instead ignore the new information and stick to what they have only gathered. This would need to be tackled in areas such as the actual communication between robots, or in how each robot interprets new information from other robots and in the process of generating the "genotypes" of each robot.

3.3 Credit Assignment Problem

What also needs to be considered with the collective behaviour of the robotic swarm, is their ability to make a collective estimation from limited communication and information. The robotic swarm, will at the end of each generation share the information they have gathered about their local area to the rest of the swarm and individual robots will also do this during their lifespan to neighbouring robots, however, the information that is shared will not be very detailed since the robots themselves only interpret their environments in a simplified way. Therefore, it is important that the swarm be able to make estimations based on the information it has at the time, and that it will be a decision that takes all robots information into consideration, in order to make the most informed decision possible as described by both Shan and Mostaghim (2021) [18] and Moussa and Beltrame (2020) [19].

In the paper by Gillala, et al, (2021) [20], they describe the problems and importance classification of data can have in machine learning models. They go on to discuss how misclassification of data can leads to issues where the key characteristics us as researchers are looking for or want to become prevalent in the machine learning algorithm tend not to be shown fairly in the results due to this misclassification. We would need to combat this problem of misclassification, so that in cases where there minority classes in the dataset which we may have interest in they would be properly represented in our results, or in the case of robot swarm generation, the characteristics of these minority classes would be present in future generation of the swarm. We can handle this problem by manipulating the credit assignment at the end of each simulation lifetime to assign more credits to individuals who represent unique behaviour, and can help with quality diversity in the swarm in the future.

In particular with heterogenous swarms, where some individuals may perform different based on their design and controller, having separate metrics to evaluate the performance of these different designs can lead to swarm generation which does not converge onto a homogenous robotic swarm. But this change to the evaluation metric must not come at a cost, where underperforming individuals are overvalued and their design is kept and passed on to future generations, a balance will need to be found.

3.4 Specialization

In this section we will discuss the importance of task specialization and distribution amongst the robot swarm, he reason for it being an important topic is due to there needing to be a distinct clarification between tasks that an individual robot can do and how a robotics swarm would handle the same tasks. One of the issues of implementing swarm robotics, is actually creating an environment where the robots would act as a swarm. As we have previously shown, there are certain collective behaviours that we want the swarm to exhibit, in order for it to be classified as a swarm. Looking at the work done by Bayindir (2016) [27], we can see that in order to accomplish this goal, we will need to ensure that swarm design methods are identified and that work is divided into task-specific categories, which individuals of the swarm will be able to accomplish.

During the lifetime of the robotic swarm, the robots will try and complete an overall environmental objective, determined by the user. However, this task itself would need to be broken up into specific parts. And it is possible that during the lifetime of the swarm, there are times when a certain subtask is of a higher priority than the others. So the important thing to do here would be able to identify as a collective how many robots are doing any particular sub-task and the swarm should be keeping aware of when the time to shift robots around to other jobs is necessary. Being able to adapt like this based on the new information received by the robots would be important for the swarm to act out its overall objective efficiently as described by Shan and Mostaghim (2021) [21].

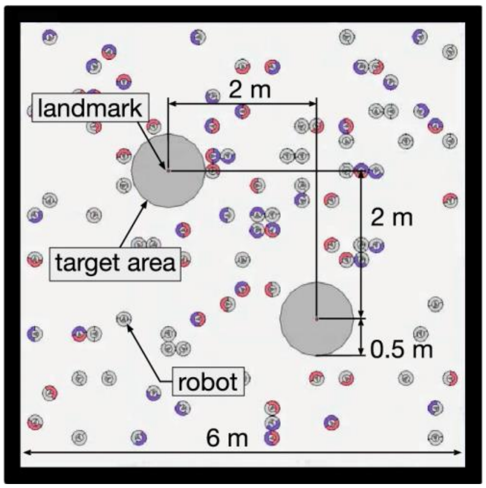

Figure 2: A representation of a task environment overpopulated by robots in a swarm by Hiraga, et al (2018) [22].

What also needs to be considered is the impact individual robots can have on each other during the course of normal activity. As described by Hiraga, et al, (2018) [22], during the course of normal activity in a swarm, other robots can have both a positive or negative impact on the work done by any individual. Further describing how due to the presence of multiple robots in what can be consider limited spaces, congestions can impact the effectiveness of an individual robot. This would be counteractive to the purpose of a robotic swarm, which wants the collective swarm to be significantly more effective than if individual robots were to carry out the task. We will need to ensure that in their specialization algorithm, when individuals and that swarm as a whole are being evaluated, we would need to ensure they specialize with either maximum cooperation, or minimum interference. By handling either of these scenarios, we can make it such that individuals in the swarm do not interfere with other individuals in the swarm.

Based on the work described by Lee and DaeEun (2019) [24], one way to handle task diversification and task distributions is to handle task distribution based on observations made by individual robots in its environment and based on information it has received from its neighbours in the swarm. Further Lee and DaeEun, describe that task allocation is determined by an individual analyzing a task list which records what tasks other robots in the swarm are currently handling. This resulting in the task distributions being more evenly distributed among the swarm and resolving the issue of too many robots handling the same task. This can reduce the impact of having too many robots assigned to the same task in the same local environment, which as seen in the previous paragraph as described by Hiraga, et al, (2018) [22], can lead to interference between individuals of the swarm.

4 Testing the Hybridized Algorithms

In order to do a proper evaluation of the combined mEDEA and Map-Elites algorithms, we would need to do a comparison of how effective they are when combined and when they are used separately. From the paper by Hart, Steyven and Paechter (2018) [9] we see that they have created a collection of 4 different algorithms to test the effectiveness of, and each on of them is compared against using a mEDEA algorithm by itself. Following a similar pattern would allow us to see if the combined algorithm truly does make a significant difference to the overall effectiveness of the swarm to its environment and help us make a conclusion on whether or not it is worth using a combined algorithm instead of the two algorithms separately.

For the testing, we will be comparing three different combined algorithms, in a variety of different environments. The algorithms we will be looking at, include the hybrid Map-elites, but also a hybrid Novel search and a hybrid Novel search with local competition. We will also alter the environments, make them more challenging for the swarm, in order to test how effective their collaborative capabilities are.

5 Collective Behaviour Applications

As a group, the robots should have tasks assigned to them, some form of assessment which can them be used to run a fitness test and determine quantitatively how well-adapted the swarm is for its environment and if the robots in the swarm are becoming better suited for the tasks. There are two task environments which seem fitting to test the effectiveness of the swarms collective behaviour applications, these task environments are a collective foraging task and a collective construction task, foraging as mentioned by Nguyen and Banerjee (2022) [25] and collective construction mention by Nitschke, Schut and Eiben (2011) [26].

In both of these task environments, we will be able to monitor the effectiveness of the collective behaviours as shown in figure 1 of section 2. Specifically, taking a closer look at the sub-categories of the list. For each task environment, there may be different behaviours which can result in a more adaptive swarm, therefore, it would be important to monitor the swarm's behaviours during the course of the experiment to determine which behaviours should be focused on.

5.1 Collective Foraging

As described in the paper by Nguyen and Banerjee (2022) [25], foraging is a task which focuses on the swarm, identifying a type of resource in the environment and them relocating it to a target area which the swarm may also have to identify in the environment. A task like this is important because it can be used to test both the individual and collective capabilities of the robots. In each generation, it tests their ability to communicate and locate high-value targets (resources and target areas) in the environment. An ability that we as testers would want to improve over time per generation. It would also be able to test the capabilities of cooperation of the swarm, in cases where in order to forage we would need multiple robots to move the object, or in cases where robots may be moving a resource from opposite sides and actually hindering the other. We would want to test how well the swarm can handle these types of events. In order to test this we would create multiple scenarios or increasing task complexity, to test the effectiveness of our algorithms and methods to completing these tasks.

Based on this, looking at the list of possible collective behaviours we would monitor, the category of swarm navigation would be one of the more important areas to focus. With its sub-categories as stated by Schranz, et al (2020) [11], of collective exploration which is described as cooperative movement through the environment to explore it; collective transport, in which the robots are able to move objects which are too large or too heavy together; and collective localization, which allows the robots in the swarm to orientate themselves based on the positions of other robots, a technique which could be useful in information sharing about resources found in the environment in relation to where a robot is.

The other collective behaviour we would be closely monitoring is the swarm's decision-making behaviour. We would want to ensure that behaviours such as: task allocation, which can be used to ensure we maximize performance of the swarm; collective perception, which would be needed for the swarm to make well-informed decisions; group size regulation, to ensure that no one resource is occupying too many robots in the swarm and reduing efficiency; and synchronization, which we can use to help coordinate tasks that require multiple robots.

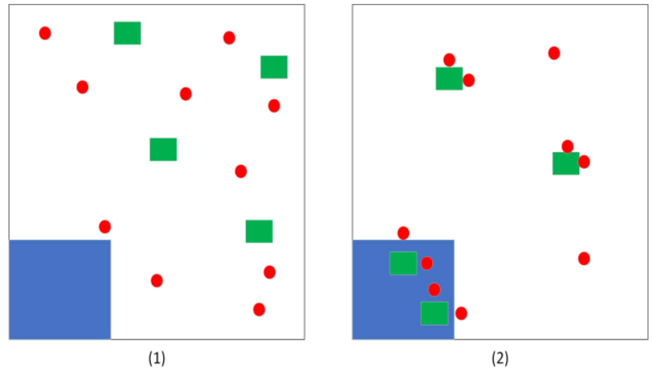

Figure 5: Collective foraging represented by agents (red) searching the environment for resources (green) and depositing them in the target area (blue).

5.2 Collective Construction

In the paper described by Nitchke, Schut and Eiben (2011) [26], the task of collective construction is described as robots in the swarm would gather resource objects and place them in the target area in a specific sequence to build a predefined structure. We would treat this as an extension of the foraging task mentioned in section 5.1. With it we would be able to test the ability of robots in the swarm to move and orientate resources in the environment. Requiring higher levels of cooperation between robots in the swarm and testing the limits of how well they are able to orientate these objects with respect to one another. Again, we would be creating multiple levels of complexity for this task environment.

Again looking at the list of collective behaviours we would be monitoring, we can see that collective construction would also require us to look at the collective behaviours of navigation and task allocation closely, in a similar way that it was done in collective foraging. This is understandable since the collective construction task environment itself is an extension of the collective foraging task environment. But it can be said that, for certain behaviours such as collective perception, it may have a stronger focus. Since we would want the swarm to have a clearer and more concise understanding of its surroundings when depositing the resources into the target area and putting them in the correct orientation.

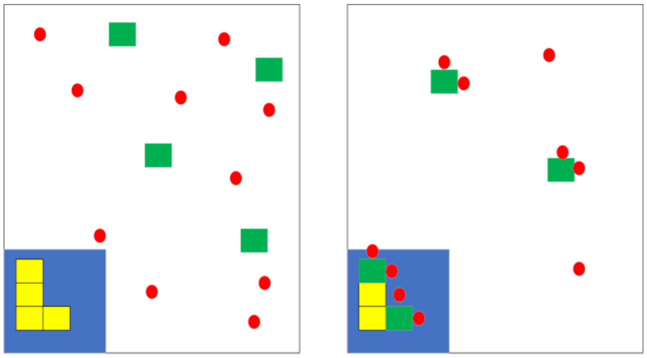

Figure 4: Collective Gathering represented by agents (red) searching the environment for resources (green) and depositing them in the target area (blue) in a specified orientation (yellow).

6 Discussion

To summarise, in order to create a hybridized version of the mEDEA and multi-BC Map-Elites algorithms, there are many factors that need to be taken into consideration. The design of the individual robot and their controller is important as this will be what determines how the robot functions in its environment, as well as, how effectively it functions in its environment. We need to ensure that individual robots are capable of proper communication between individuals, that they can make informed decisions, that they can gather relevant information about their surroundings. It is important ensuring that individuals function as intended, however, besides just the individual behaviour of the robots their collective behaviour, collective controller and abilities to work as a swarm is also important. For their collective behaviour we need to ensure that with each new generation the swarm is adapting better to its environment. That the evolutionary algorithm is able to make good assumptions about which characteristics would be best suited for the environment and can mould future generations of the swarm from this.

From the research conducted it must be noted that there are certain short fallings in the current literature. I have found that although when viewed in conjunction the sources I used to carry out this literature review do handle most of the gaps in the literature, in isolation when reading them as their own reports or research papers some are lacking in covering enough of the variables. For example in the paper by Hart, Syeyven and Peachter [9] they design and test their algorithms effectively and plot the results against a base mEDEA algorithm, however, there is little to no mention on reducing noise in the data used like in the paper by Shan & Mostaghim [18]. Overall, I found that many of the papers do not take this into consideration when covering how they handled their data and when they drew conclusions from it. It can also be said that in some of the papers, when they tested their Map-elite algorithms and mEDEa algorithms, they showed little to no information on how they handled task diversification. A concept which is very important, if we are to create a highly adaptable and efficient robotic swarm. In the literature I reviewed, there was also little mention of how the environments used were designed, many of the papers mention then need for the swarm to be adaptive to unknown environments, but not many of the papers covered how they created handled this factor, or if they generated new environments to ensure the algorithm was effective across those environments either. This is something we would need to look into and consider.

However, I believe that in my research paper, I will be able to mention how these problems were handled and which of their aspects did prove to be problematic or which had minimal effect on the experiments and results of the project. I also believe that regarding this field of study, additional attention should be given environment generation. Based on how there a lot of work, research and experiments has been done testing if swarm can become well adapted to unknown environments, I believe these same experiments should be conducted in cases where there is more complex environments. As this could differentiate if these algorithms are well adapted to evolve swarms in simple or complex environments. Although, this kind of research would not have much to do with swarm robotics, collective behaviour or evolutionary algorithms, I believe that one of the areas holding back real-world implementation of swarm robotic technology is a lack of trust in the results of simulations, so if it is possible to show that swarm robotics is able to work in simulated environments of increasing complexity, more credibility can be given to the simulations. Allowing for the fields of swarm robotics to provide more valid results of its effectiveness.

In term of beneficial ideas and information found, I came across a few papers which my hybrid algorithm would have similarities with, such as Hart, et al [6]. I would be able to use the research they have done and build up from there. I was also able to uncover different ways to handle communication between robots and between generations, how to handle issues with noise in the data, and the start of how to handle things like collective estimation.

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