AS Assessment 2: Adaptive Behaviour in Swarms

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Abstract

With an ever expanding workforce of automated machines in our society it is pivotal that we employ communication systems which allow for fast and accurate estimations in a changing environment. An Internet of Vehicles is just one example of a network which must efficiently pass information both locally and globally. In this report I extend the work of Aust et al[1] which investigates optimal communication strategies for swarms on a collective detection task in a changing environment. I build on this work by investigating the swarms ability to adapt to a gradually changing environment.

Introduction

The area of collective decision making is one which has been investigated from a number of viewpoints, with applications which are set to increase in number as we continue to make progress in the development of robotics and deployment of networks of communicating machines. It is conceivable that swarm robotics could revolutionise a number of industries - examples include farming and agriculture[2], as well as search and rescue[3].

Much of the work done within swarm robotics has resulted from observing social species such as birds, ants, and bees. Each of these animals utilise collective action in varying ways which provide greater advantages than if they were to simply act alone. Take ants as an example, certain species employ distributed decision making to quickly and accurately find a new nest of suitable quality[4]. The mechanism that they use naturally uses positive feedback to propagate information and lead to colony wide decisions from local information. These mechanisms have developed to aid the species in survival, in a similar way we may wish to optimise designed distributed systems to perform a particular task, potentially in a changing environment.

This brings us to the topic of adaptation, and requires us to take a brief aside to address semantics. Firstly, I define a *system* following the train of thought of Meadows[5]. A system is a set of elements which are interconnected and produce a characteristic behaviour. Meadows states that the characteristic behaviour may be called the system's "function" or "purpose", this tends to lead into philosophical debates of purpose and meaning. However, for the purposes of this report, we are interested in designing systems for a specific and well defined purpose, and so do not linger on this point. *Adaptation* is another term which must be defined due to varying usage throughout the literature. I accept the use of the term adaptation to refer both to a process by which an adaptive trait comes into existence, and also to the trait itself. As exemplified by Mayr's notes[6] on the subject, there are those that argue the process definition is a misuse of the word. Throughout the report I will be clear in my language as to which meaning I refer to. Finally, I also make the distinction that a system which can adapt itself is called a self-adaptive system. As opposed to a system which is adapted through interaction with another system.

Aust et al[1] build on previous work investigating the mechanisms of swarm robotics which allow the collective to "self organise and to ensure that 'more is different'". There are numerous parameters which may affect the efficacy of a collective with regards to a task. Aust et al demonstrate and provide mathematical reasoning for a phenomenon they call the Less is More Effect (LIME) - which relates to the counter-intuitive observation that less communication between individuals may actually improve the groups ability to carry out the process of adaptation. They demonstrate this effect in a collective perception scenario, where a group of robots with local sensing must provide a global judgement for which colour makes up the majority of the environment. I work with this environment to replicate and extend their results to better understand factors which affect a swarms adaptive process capabilities.

I adjust the dynamics of the environment to allow for gradual change, as opposed to the large step change which occurred in Aust et al. The system is then investigated to determine which factors affect adaptability - can the swarm provide information indicating gradual change, or is it limited to identifying step changes? The utility of communication is also considered through carrying out baseline simulations in which no communication is used.

The replication resulted in pivotal questions needing to be asked related to methodology used by Aust et al[1], as well as results which were not in support of their findings. Although it is noted that this inconsistency in results may well be due to lack of methodological detail. Experiments containing the gradually changing environment produce interesting insights which highlight unique advantages for both short and long range communication in the system.

In the following text I will first outline the methodology, including a detailed description of the dynamics of the robots and environment. I will then define the tests which I will carry out along with their associated hypothesis. Finally, I discuss the findings to highlight key insights, downfalls and direction for further work.

Methods

Robots

Following the setup of Aust et al[1] each robot is modelled as a finite-state machine which executes a number of subroutines in parallel to determine its action. As a simplification, I do not account for collisions of the robots, and so they simply move as if other robots provide no barrier to movement.

Finite-State Machine

Based on self-sourced and social evidence a robot may change its current state.

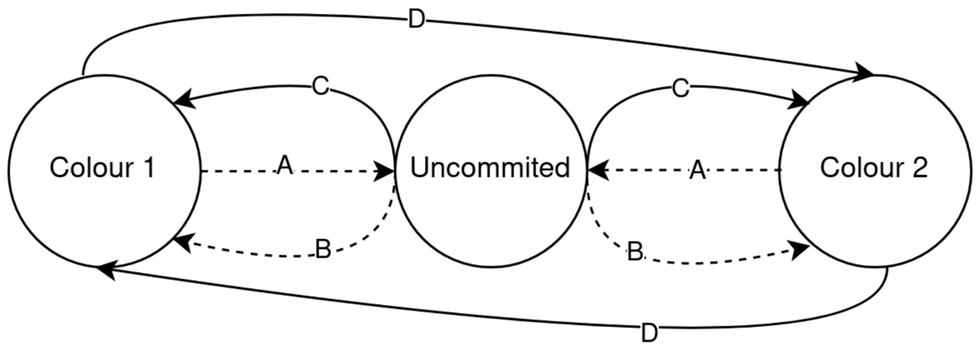

Figure 1. Finite-state machine representation of a robot. Dashed lines represent a state transition due to social information, Solid lines are transitions due to self-sourced information. A: Cross-Inhibition - A committed robot becomes uncommitted when it updates based on a neighbour's conflicting opinion. B: Recruitment - An uncommitted robot commits to the colour of a neighbours recruitment message. C: Discovery - An uncommitted robot commits to the colour found in the sample cycle. D: Direct Switching - A committed robot switches colour based on sampling a colour of greater concentration than its current committed colour. The robot can also stay in the same state (not depicted in the graphic) if there is no evidence given to change its state.

Subroutines

Movement

Each robot's movement is controlled by a Random Waypoint Model - described in detail by Bettstetter et al[7]. The robot selects a point uniformly at random from within the grid and travels to this point. This random selection is done by sampling from two uniform distributions, one for the x-axis position, and one for the y-axis position. Upon reaching the waypoint it repeats this process. The robot travels at constant speed and takes a direct path to each waypoint.

Sampling

Each robot carries out a sampling cycle which contains s_l samples, with an interval of τ_s between samples. Each cycle the robot selects a colour that it will estimate the concentration of through sampling. In most cases, the robot simply chooses the colour of the square that it occupies at the end of a cycle as the sampling colour for the next cycle. This is true unless the robot is recruited, where it will immediately sample the colour it has been recruited to. Each sample returns a binary result: 1 if the square was the sample colour, 0 if not. If the robot was sampling the colour that it is committed to, then it will update its concentration estimate of that colour. If it is sampling a different colour and it obtained an estimate of greater concentration than the committed colour estimate, it may then use this as self-sourced evidence to switch state. When sampling after a recruitment, the robot will update its committed colour estimation with each sample to $\hat{q}_+/s$ - where $\hat{q}_+$ is the current number of sampled squares that were the committed colour. This allows the robot to regulate its broadcasting frequency based on its confidence in the neighbours opinion. For sample cycles not immediately after recruitment, the concentration estimate will only be updated after the current cycle ends.

Broadcasting

Each robot that is committed to a colour will broadcast its opinion at a frequency f to neighbours within a range r_c. f is based on the robots concentration estimate of the colour it is committed to - higher frequencies indicate greater concentration estimates. The broadcast frequency is calculated as $f = 2\, min(2\hat{q}, 1)$, where $\hat{q} = \hat{q}_+/s$ is the current concentration estimate from the last cycle sampling the committed colour. Hence, a robot broadcasts with maximum frequency of 2Hz if its concentration estimate is greater than 50%. Otherwise, it will broadcast at a lower frequency, indicating that it is less confident in its opinion.

Opinion Update

At an interval of τ_u the robot will consider whether it should change state based on social and self-sourced information. If the robot has only received social evidence within the last τ_u seconds, then it can undergo two types of transition based on its current state. If it is uncommitted, then it will undergo a *recruitment* transition to the colour of the neighbours message. If it is committed to a colour, it will undergo a *cross-inhibition* transition where it will then become uncommitted. If the robot receives only self-sourced evidence within the last τ_u seconds then it has one possible type of transition. The robot will undergo a *discovery* transition, where it will swap to the colour that it sampled no matter what state it is in. It should be noted that the robot is only said to have self-sourced evidence if it obtains a "better" concentration estimate. An uncommitted robot will perceive any non-zero sample as better, and a committed robot will perceive a higher concentration estimate as better. Each of these transitions can be seen in Figure 1.

Environment

The environment is a grid of coloured squares that the robots may move around on and sample. Proportions of the size of the environment, speed of the robots and other factors which rely on one another have been set to resemble the conditions of Aust et al[1]. Effectively the robots travel a fifth of a square per second - similar in magnitude to Aust et al in that each square is 5cm by 5cm and robots travel in a straight line at about 1 cm/s. The environment grid contains 20 by 40 squares, each of which can be set to 1 of n colours. When creating an environment with a certain proportion of squares for each colour, a uniform sampling procedure takes place for each square. For example, if an environment is to be 70% orange and 30% blue, then each square is assigned a colour based on weightings which result in an average of 70% orange and 30% blue. Visualisation of the environment can be seen in Figure 2.

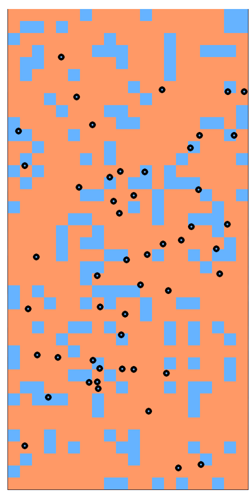

Figure 2. Environment initialised to have 70% orange squares and 30% blue squares. 50 Robots (black circles) are seen in the environment - each has a light which displays the colour it is currently committed to. If it is uncommitted there will be no indicator.

Gradual Change

In order to test the adaptability of the swarm in dynamic conditions I also implement a gradually changing environment. Given a final colour distribution and a length of time for the changes to occur, the environment will update such that there is a smooth transition from starting colour distribution to the final colour distribution. At a set environmental change interval, τ_e, the grid will be regenerated with an updated colour distribution - gradually moving closer to the end colour distribution.

Results

Replication of Aust et al[1]

The first experiments I ran related to investigating the LIME as demonstrated by Aust et al. The results obtained in the current study have large quantitative and qualitative differences compared to previous work. Reasons for which are hypothesised in the discussion below, as well as further analysis of qualitative observations. In all tests, each robot starts with an 80% chance of initially sampling blue, and a 20% chance of initially sampling orange.

Test 1 - Less is More Effect

Parameter	Value
Orange Square Proportion	0.9
Blue Square Proportion	0.1
Grid Size	20 by 40
τ_u, update interval	1s
τ_s, sample interval	4s
Sample cycle length	15
Number of Robots	50
Starting Robot decision state	2 (Blue)
Starting Robot concentration estimate	0.8
Robot Speed	1 cm/s

Table 1. Parameterisation for test 1

Using the experimental setup described in Table 1, communication range, r_c, is taken as the independent variable and is varied through a range of 2.5cm $\leq r_c \leq$ 225cm. All other variables were controlled.

Aust et al[1] do not provide sufficient details of pertinent experimental information and so comparison does not yield informative conclusions. Missing information includes the cutoff for the adaption process - meaning the time after which a run is declared to have not adapted if it has not reached the correct conclusion. Here I present an independent analysis of the data, using a cut-off time of 1000 seconds.

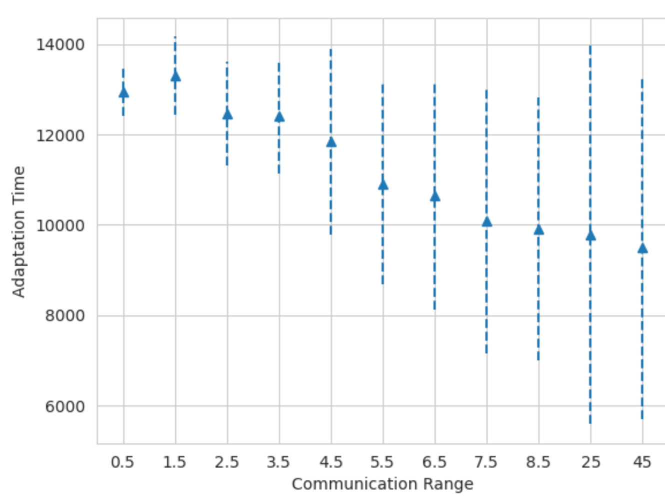

Figure 3. Mean adaptation time over 30 runs for varying communication ranges. Standard deviation is plotted as the dashed lines for each communication range value. Environment was initiated with 90% orange tiles and 10% blue tiles, with each robot committed to blue with concentration estimate 80% - hence, simulating a sudden step change in the environment from majority blue to majority orange. Greater communication range appears to reduce adaptation time on average. Y-axis is seconds * 100.

Unlike Aust et al[1], all runs successfully adapted and stabilised on the correct majority colour decision. In order to investigate the effect of differing levels of communication I use the time to adaptation as an indicator of performance. A collective is deemed to have adapted if 70% or more robots are committed to the correct state (the state which represents the majority colour in the environment) for a period of two minutes without fault. The adaptation time is the start of this two minute period. As seen in Figure 3 it appears that there may actually be an advantage related to greater communication range in this setup. Low communication ranges provide consistent adaptation times shown by the low standard deviation, however greater communication ranges produce lower adaptation time on average.

Reasoning for greater communication range being beneficial in this situation relates to the faster spread of opinion change throughout the population. Figure 4 illustrates this faster spread of information. A large spike in uncommitted robots occurs for the 42.5cm communication range, compared to only a minimal change in the 7.5cm simulation. The greater proportion of uncommitted robots lowers the broadcast of the, now wrong, majority blue opinion. Thinking in terms of systems, it can be said that there is a positive feedback loop which acts to spread information. The greater communication range has greater amplification and so the opinion change is more likely to propagate and at greater speed.

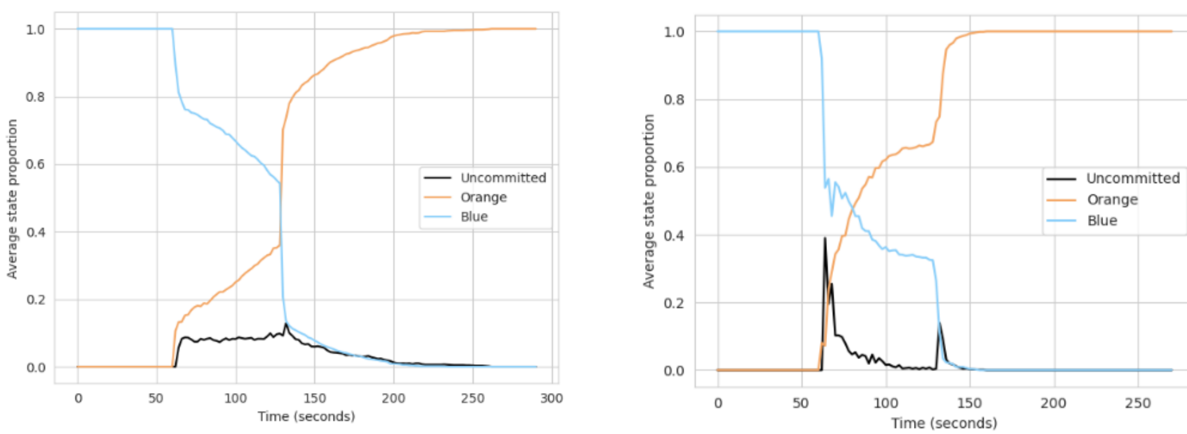

Figure 4. Average state proportions for test 1 setup. Left) Communication range of 7.5cm (1.5 squares), Right) Communication range of 42.5cm (8.5 squares). The effect of greater communication range is seen through the high change in states at the 60 second mark for the 42.5cm range. At this point in time, a majority of robots will have just sampled orange and likely discovered that it is of a higher concentration than blue - the higher communication range increases the speed at which this information travels throughout the swarm.

Test 2 - Impact of communication

As a means to further understand interactions within the system I carried out simulations in which robots had no communication. This aids in extracting the impact of communication frequency on the swarms capabilities. The same parameter setup as in Table 1 was used apart from the following: communication range was held at 0 for all trials, τ_s was varied as the independent variable through the range of 1 to 45 squares (5cm to 225cm). Results shown in Figure 5 indicate the general trend that lower sample cycle lengths result in lower adaptation times. Note that a sample cycle length of 1 does not follow this trend - robots opinions are highly variable and so random fluctuations are more likely to occur. It is interesting to explore the relationship between problem difficulty and effectiveness given different sample cycle lengths. Hypothetically, it seems intuitive that greater problem difficulty will lead to short sample cycle lengths becoming less effective. This would result in the optimum value being shifted right along the x-axis.

With regards to the effectiveness of communication, the adaptation time for the sample cycle length of 15 can be compared to results from Test 1. From Figure 5 we can see that the average adaptation time without communication is 190 seconds. Referring back to Figure 3 we see that every communication range tested resulted in a quicker adaptation time than no communication. Hence, in this setup, the additional amplification effect of communication aids adaptation.

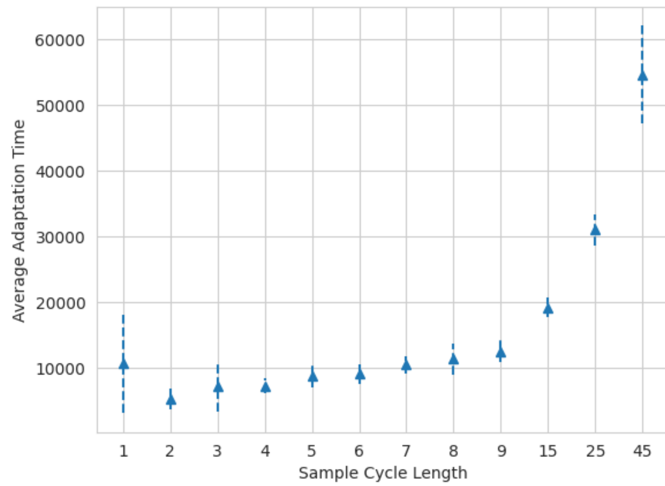

Figure 5. Average adaptation time for varying sample cycle lengths, where robots had no communication. Standard deviation is plotted as the dashed lines for each communication range value. For an easy decision problem which has a large proportion majority colour, lower sample sizes are sufficient to result in the majority of robots making the correct state decision. This leads to reduced adaptation times as information about the environment is quick to be acted upon by robots, as opposed to longer sample times where there is greater delay. Y-axis is seconds * 100.

Extension

Test 3 - Adaptation to Gradual Change

Instead of an immediate step change in the environment, we now consider a gradual change. Robots start in the correct decision state of majority blue, but then the environment gradually changes to an orange majority. Analysis of interest relates to identifying if the system can sense gradual change significantly before the final state is reached - which it is known to be able to adapt to as shown in Test 1.

Looking at adaptation times, as in Figure 6, there is again a notable trend that greater communication range results in a lower average adaptation time. Furthermore, the system was only able to adapt before the completion of the changing environment with larger communication times (greater than 7.5), and only in a minority of these cases. Adaptation time is not the only statistic of relevance, further insight can be gained by analysing average state proportions throughout simulations.

Lower communication ranges appear to have properties which are useful for indicating change and uncertainty in the environment state. Figure 7 compares a communication range of 2.5cm against 225cm. With a communication range of 225cm we see spikes of increasing size of uncommitted robots, until eventually a step change happens and the population converts to a majority orange. After each initial spike there is a rapid regression back to the original opinion - a result of a majority committed to blue being able to silence the minority. Contrastingly, the system with robot communication ranges of 2.5cm displays a much smoother transition of opinion. As the environment state reaches 0.5 there is a steady increase in the number of uncommitted robots - representative of the systems uncertainty of the majority colour.

Parameter	Value
Orange Square Start Proportion	0.3
Blue Square Start Proportion	0.7
Orange Square End Proportion	0.7
Blue Square End Proportion	0.3
Start of gradual change	0s
End of gradual change	360s
Change interval, τ_e	3s

Table 2. Parameterisation for test 3. Parameters not mentioned are the same as in Table 1.

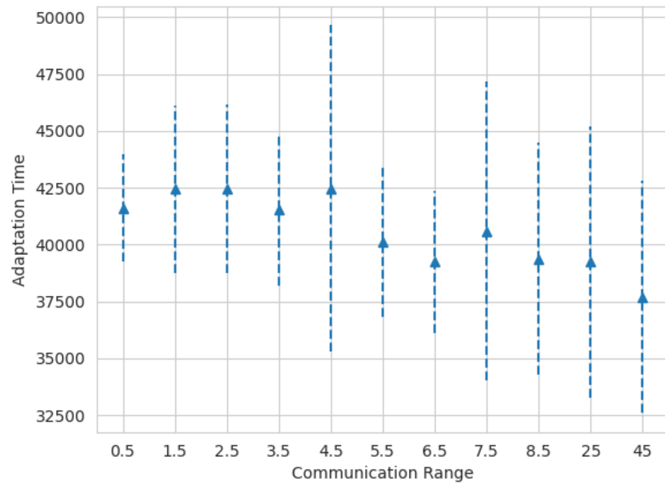

Figure 6. Effect of communication range on adaptation time in a gradually changing environment. Standard deviation is plotted as the dashed lines for each communication range value. Y-axis is seconds*100. Similarly to Figure 3, we see a slight trend of decreasing mean adaptation time as communication range increases. The gradual change is completed at 360s, and only a minority of higher communication range simulations manage to adapt before this point.

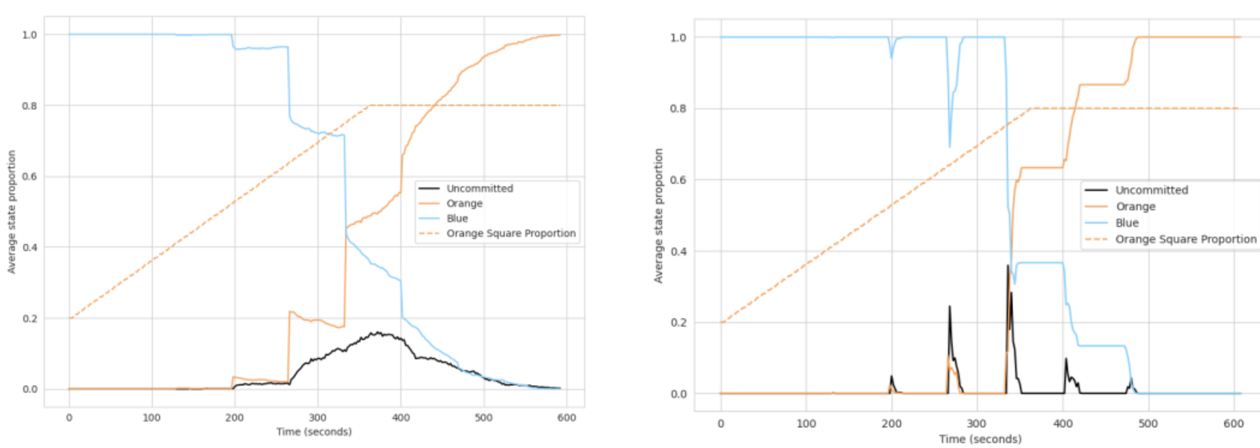

Figure 7. Comparison of communication range 2.5cm (left) against communication range 225cm (right) for an environment which gradually transitions to a majority orange state. The larger communication range produces marginally faster adaptation on average due to rapid information transfer. Although the smaller communication range adapts slower, the state of the robots may actually be more informative as to the changing environment.

Discussion

The main aim of this report was to replicate and extend the work of Aust et al[1] - providing insight related to the nature of interactions and their effects within a collective. I shall first discuss the outcomes of the replication experiment and possible reasoning for the lack of consistency in results. I will then discuss the extension relating to the gradually changing environment, and how this relates to the literature. Finally, I will highlight key areas for further work relating to this paper.

Simulations investigating the effects of differing frequency of interactions throughout the swarm led to results which did not support the conclusions made by Aust et al. The Less Is More effect proposes that less frequent communication leads to greater adaptability in a swarm - i.e. changes in environmental information are more likely to be perceived by the group. However, in my experiments there was a clear opposite trend that increased communication range led to greater adaptability. Suggesting that more is indeed more. Experimentation of greater depth is needed before conclusions can be made, but these results provoke questions regarding the experimental setup of Aust et al. There are several key missing pieces of methodological information which lead to irreproducible results.

First of all, the initial state of each robot is not clearly defined - details of the robot's sampling colour are not included. The initial conditions are set such that immediately preceding time step 0 there has been a step change in majority colour, as indicated by the state of the robots and their concentration estimates. Following on from this, it makes sense that a majority of robots would be sampling for blue, due to the methods defined in the sampling routine of each robot. This is the initial condition that I have used in my experiments and all parameter setups tested managed to converge on a correct decision. From my own experimentation, swarms were less effective at adapting if their initial sampling colour was selected based on the environment state at time step 0 - possibly a method employed by Aust et al. Many swarms with this initial condition failed to adapt within the allotted 1000 seconds as only a minority sample blue to update their concentration estimate. Using this method violates the idea of a step change having just occurred and tests against a contrived difficulty. The other lacking detail is the cut-off point for determining if a swarm has adapted. This has obvious implications in that longer-run behaviour may result in different outcomes.

The extension relating to detecting gradual change in environments produced interesting results that build upon current literature. Within this collective system, short and long communication ranges appeared to have unique advantages with regard to detecting change. Short range systems were able to indicate uncertainty in the majority colour through the increase in uncommitted robots, whereas long communication ranges enabled faster majority adoption of new environmental state information. In the focal paper[1], Aust et al discuss the idea that a minority opinion can be squashed by the majority and this can be seen in Figure 7 for the high communication range. However, with large sampling times and movement simulating random dispersion this is only an issue for certain types of environmental change. Sufficiently slow environmental change - as in test 3 - coupled with long sample cycle length leads to self-sourced information of high accuracy. In a situation like this, communication only serves to speed up decisions.

Relating to the last point, it would be of interest to explore a similar system but with varying rates of environmental change. I hypothesise that faster environmental change would likely result in systems that more heavily rely on social evidence through communication due to a single robot's lack of ability to cover the rapidly changing environment. Another area for future work would be the extension of the collective to a larger self-adaptive system through the use of a subsystem which could alter robot behaviour in response to environmental feedback. For example, by monitoring for spikes in uncommitted robots, the system could lower the communication range in order to gain more information regarding the uncertainty of the majority colour.

Additional Figures

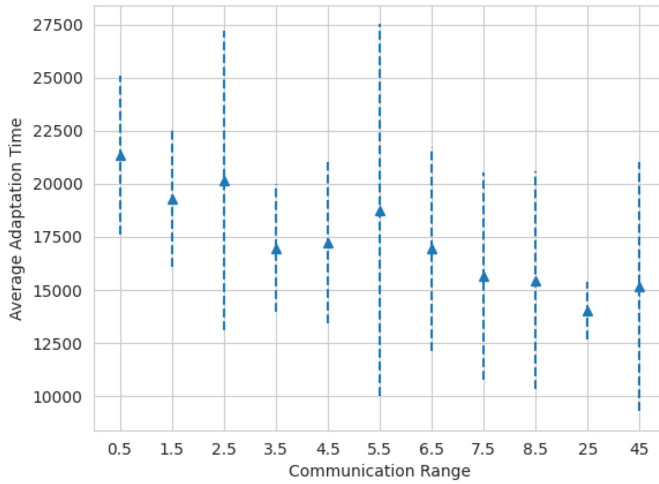

Figure 8. Test 1 average adaptation times using a more difficult environment - 70% orange and 30% Blue. Standard deviation is plotted as dashed error bars. The same trend of decreasing adaptation time for larger communication ranges is present.

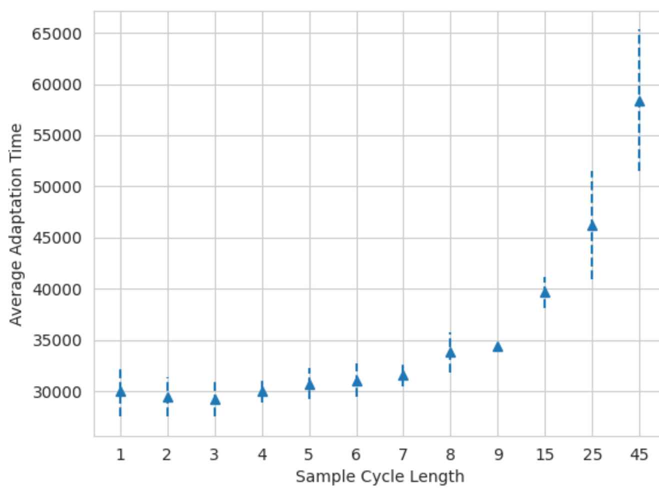

Figure 9. Effect of varying sample cycle length in the gradually changing environment with no communication between robots. Standard deviation is plotted as dashed error bars. Lower sample cycle lengths result in lower adaptation times.

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