Drone Self Assembly

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Abstract

With technology advances, fully autonomous drones are becoming popular and assembling the swarms of autonomous drones in a particular zone is a challenging task. In this paper, we present a multiagent system design of Drones Self Assembly. In our simulation, we model a simple grid-based space in which the desired region is a drawing marked with flags. We seek to achieve the self-assembly of autonomous drones to replicate the provided drawing without collision and as quickly as possible. Different map sharing strategies and communication radius are used along with the noise introduced in map sharing to investigate their effects on the completion time. We conduct a series of experiments to test the effectiveness of our design and analyze the results.

1. Introduction

We designed our agents to make primarily local decisions based on the perception of a local area but still try to achieve emergent behavior. The decision made by agents includes what direction drone should take to reach a nearest desired location and to avoid collisions by interacting with the agents in the communication square. Our desired emergent behavior includes: (1) replicating the drawing by occupying all the flag positions, (2) occupying all the flagged positions as fast as possible. We created a set of hypotheses that defines how different environmental parameters like the edge of the communication square, map sharing strategies among agents, and the noise level in the map sharing would influence emergent behavior and conducted a set of experiments to verify our hypotheses.

The rest of this report is organized as follows: In Section 2, we present an overview of our system design, including the design and implementation of both the environment and our agents, as well as a little more detail on the desired emergent behavior from the agents' decisions. In addition, managing a group of autonomous drones in a collaborative task environment is challenging and requires a framework to impose rules that govern the behavior of the group as a whole. In order to test the effects of local decision making leading to emergent coherent global behaviors, we have designed simulations involving assembly of drones in a desired region where drones are supported by autonomous agents, and the desired region is marked by flags. The simulations were implemented and conducted with the Repast Simphony simulation toolkit in the Java programming language.

In Section 3, we describe our hypotheses, and in Section 4, we talk about the experiment design. Then, we present the results of our experiments and try to give justifications and implications for observed trends. In addition, we provide a discussion on the results gathered, including evaluating our hypotheses. Finally, we describe directions and avenues for future work, and we come to brief conclusions.

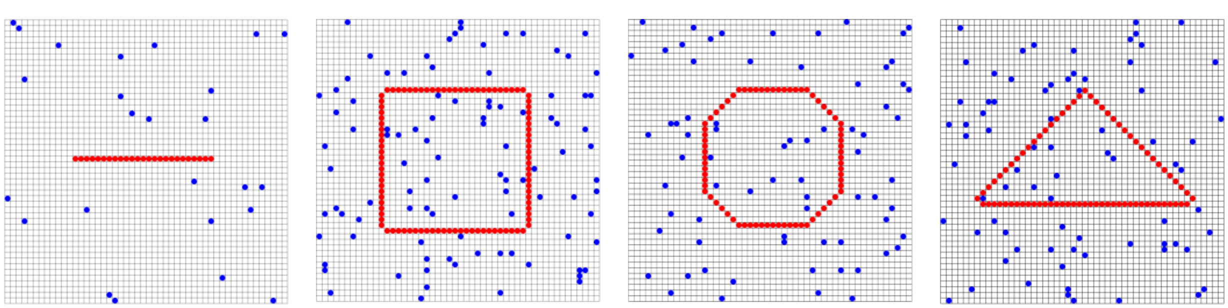
2. Simulation Design

In this section, we describe the design and implementation of our simulation. We begin by outlining the design of the environment, followed by a discussion on the design of autonomous drones, concluding with the emergent behavior desired from our simulation.

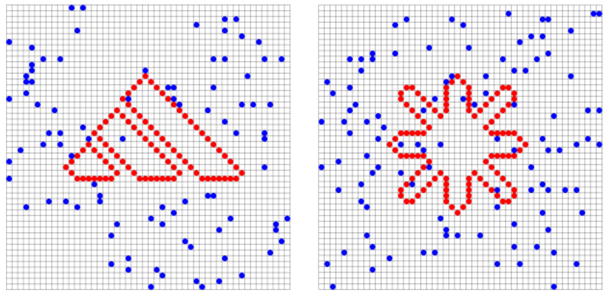
2.1 Environment Design

The environment consists of a 2-D frame and the desired region represented by a drawing. The size of the 2-D frame will be 50x50, and the drawing could occupy K pixels (K depends on the type of the drawing). Every pixel occupied by the boundary of the drawing will be marked with a flag so that drones can recognize. Each drone needs to occupy one flag, so there should be a total of K drones. It is guaranteed to have enough space for all drones to move around. Initially, each drone is located in a random position. To be optimally efficient, drones should occupy all the flagged pixels while avoiding collisions.

The input drawing can be provided in two different groups based on its structural complexity as described in Figure 1 where blue dots represent drones and red dots represent flag positions. The complexity of the drawing structure is defined by the ratio between the number of flags and the area inside of the drawings. The larger the ratio is, the more complex structure the drawing has.



Drawings from group 1 - simple-structured drawings



Drawings from group 2 - complex-structured drawings
Figure 1: Drawings in two groups

2.2 Agent Design

The agents will be designed as intelligent drones. The drones will be able to move in any vertical or horizontal directions. All drones operate at a uniform speed which is 1 pixel/tick, and they will start in unique, random locations on the frame.

For all drones, each will maintain a map of visited pixels. It helps drones correct the wrong information about the visited pixels obtained from others in the communication square and avoid exploring the pixels they have been before. Each pixel has a coordinate (x, y) where x is the row index, and y is the column index. The bottommost row and the leftmost column are indexed 0. All drones will continuously exchange their map with others drones in their communication square to try to get a full view of the whole drawing.

At every tick, a drone will choose the nearest unoccupied flag on its map and find the shortest path to get there, or if there exists no such flag, a pixel that has not been visited before will be picked. The algorithm used to find the shortest path is Breadth First Search because of its simplicity and good performance comparing to other algorithms. If there is more than one location satisfying the condition above, then one will be chosen randomly. If there is more than one drone that wants to occupy a single pixel or flag, a tie will be broken by using the clockwise rule as follow: Right > Bottom > Left > Top. That is, the drone at a higher priority direction with respect to the targeted pixel will have the chance to occupy that pixel/flag. This ordering will help to avoid collisions which will happen when two or more drones are moving to the same pixel at the same time.

The parameters to test the effectiveness of agent design are the edge of communication square, map sharing strategy, and the noise level in the information being shared. Now, we will describe each of these parameters.

2.2.1 Communication square

Each drone knows its own location on the plane and can continuously "see" as well as communicate with all drones within a square of edge 'R' centering at its own location, which is known as the communication square.

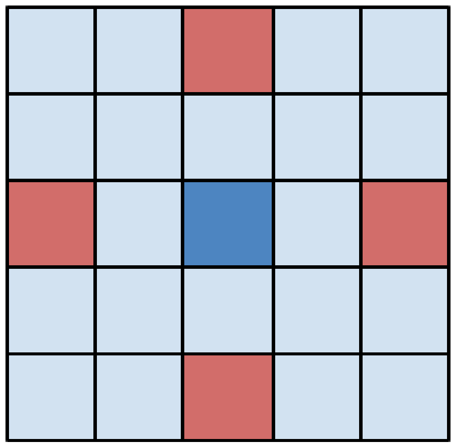


Figure 2: A communication square of edge 5.

Figure 2 represents a communication square of edge 5. It describes that the drone at the blue pixel can communicate with other drones and perceive information from the neighboring 24 pixels. The edge of at least five will be chosen because the drone needs to know what is coming to avoid collisions. The square with edge of 3 cannot tell drones what is coming from the red squares (Figure 2).

2.2.2 Map Sharing Strategies and Noise Level

Several strategies have been designed for map sharing and introducing noise which will be discussed in this section:

(a) *Map sharing strategy*: Four different strategies will be used

1) *No map*: Each drone will share no map and will just have information based on its own perception.
2) *Individual map*: Each drone will only share its own map which consists of all explored positions.
3) *Individual and Connected map*: Each drone will share the explored map and its connected portions that they got from others.
4) *Individual with both Connected and Not-connected map*: Each drone will share its own map and everything that they got from others.

b) *Incorporating Randomness (Noise)*:

The randomness is introduced in the environment by applying noise in the map sharing between drones. That is, randomly changing the values of few pixels in the map being shared with other drones. N% of noise will be applied.

Drones will use their maps as well as maps that they got from others to complete their tasks. However, because of noise during communication, drones will be able to check for valid information and update the maps based on their own observation from the environment. For instance, as a drone observes a flagged location during its searching process, the state of that location will never be changed to an empty location through communication regardless of noise. In addition, if there exist some conflicts between information through communication, the state having the majority of drones support would be chosen. A random state will be chosen in case of a tie.

2.3 Emergent Behavior

The desired emergent behavior is to occupy the flagged pixels delivered to the drones perfectly in the least amount of time without causing any collision. Ideally, the drones will be able to decide themselves how to move using the map they have at each instant of time.

3. Hypotheses

In this discussion, we talk about a set of questions that we wished to explore with our simulation to evaluate the effects of environmental settings on the performance of the system and what coherent behaviors emerge as a result of the agents in the system making local decisions. We provide hypotheses for each question and an explanation for each hypothesis.

Question 1: How does the edge of the communication square affect efficiency and the time taken by drones in the system?

Hypothesis 1: At some levels of noise, the edge R of the communication square is inversely proportional to the time it takes for all drones to complete their tasks.

We expect that, with an increase in the edge of the communication square, the number of interactions also increases; thus, more information is obtained by a drone, and the more information they have, the faster the drawing can be replicated.

Question 2: How does the noise level in the map sharing affect the efficiency and time taken by drones in the system?

Hypothesis 2: We assume that the level of noise N is directly proportional to the time it takes for all drones to complete their tasks.

We expect that an increase in the noise level will lead to more inaccurate information, and drones will need to spend more time making corrections. Hence, with an increase in the noise level, the completion time will also increase.

Question 3: How does noise level, map sharing strategy, and the edge of the communication square altogether affect efficiency and time taken by drones in the system?

Hypothesis 3: At some levels of noise, the amount of information being shared might be proportional to the time it takes for all drones to complete their tasks.

We expect that the decision making is improved as in map sharing strategy (4), all the information from other drones is combined, so that drones will have more information in comparison to other strategies. Hence, at some levels of noise, strategy (4) may be the fastest. However, as the noise is applied on a percentage of the map being shared, we expect that at some other levels of noise, the more information drones get from others, the longer they need to suffer from confusions.

4. Experimental design

The experiments will be designed to test three hypotheses above. We will run numerous simulations varying drawing structure, map sharing strategy, and two variables as follow:

Variables	***Range of values***
R	5, 9, 13
N	0, 10, 20, 30, 40, 50

Table 1: Range of variables to do experiment.

For R, we choose 5 (1% of the total map), 9 (slightly less than 4% of the total map) and 13 (approximately 7% of the total map). In the general case with a large number of drones, 10% of the total information might be pretty much for each drone. Therefore, we want to see how the result will change with an observation area occupying less than 10% of the total map.

For N, we think 50% of noise should be the maximum level that we can have because an information with more than 50% of inaccuracy is not really useful. The drawing will be chosen from the two groups separated by the complexity of their structures in the Environment Design session. The map sharing strategy will be one of the four strategies introduced in the Agent Design Strategy session.

To address randomness, we will run 30 simulations for each configuration. In overall, there are a total of 6 (figures) × 4 (sharing strategies) × 3 (R) × 6 (N) × 30 = 12960 simulations that will be run.

The time it takes for all drones to replicate the drawings will be averaged for analysis as follows:

1) Data from all configurations which only vary R - the edge of the communication square will be analyzed separately to test hypothesis 1.

2) Data from all configurations which only vary N - the level of noise will be analyzed separately to test hypothesis 2.

3) All data will be used to see the relationship between N - the level of noise with R - the edge of the communication square and four map sharing strategies in order to test hypothesis 3.

We use the Recursive Porous Agent Simulation Toolkit (Repast), which borrows many concepts from the Swarm agent-based modeling toolkit, to implement our experiments. More specifically, our model is developed using Repast Simphony with the Java computer language. It supports the development of extremely flexible models of interacting agents for use on workstations and small computing clusters. The interface of the model application is shown in Figure 3.

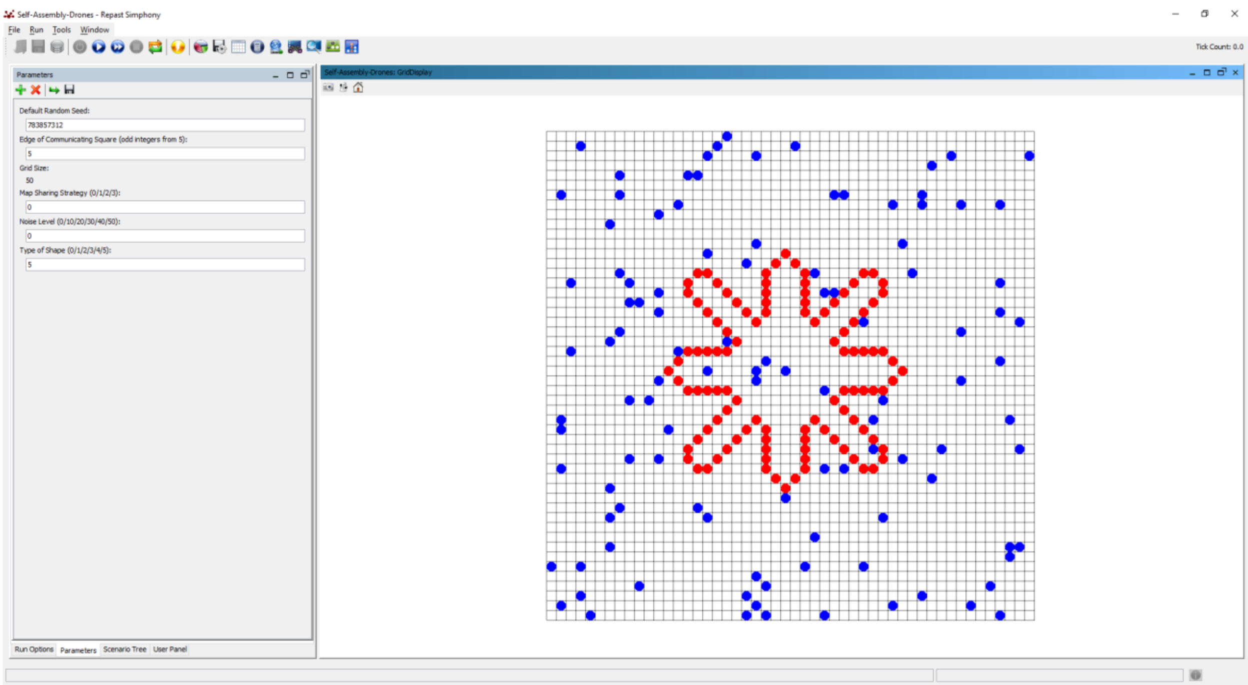


Figure 3: Application interface.

5. Results

Hypothesis 1: *At some levels of noise, the edge R of the communication square is inversely proportional to the time it takes for all drones to complete their tasks. That is, the more information they have, the faster the drawing can be replicated.*

We first assumed that increasing R would decrease the time it takes for all drones to complete their tasks and it was only true for a portion of all configurations because of the presence of noise. As we increased R, drones have more neighbors and with a high level of noise, there is more incorrect information through communication that they need to justify.

Figure 4 displays the time of completion for all configurations varying only R in the experiments which are used to test Hypothesis 1. Any vertical line in the chart represents one configuration with three completion time corresponding to three different Rs. The time is higher in the last portion of the chart as the system needs to deal with drawings of more complex structure from group 2. We observe that the time clearly decreases as we increase the edge of the communication square. However, the decrease happens for all configurations regardless of the presence of noise. We believe one factor that leads to this result is randomness, specifically in drones initial locations, drones movement, and noise application. As R increases, it is true that drones will have more neighbors to communicate with, but that case does not always happen. There still exists some cases when drones have few or even zero neighbors in their communication squares. Besides, noise is randomly applied to the information being shared, so it does not always have negative effects. As drones are capable of checking for valid information and updating their map based on their observation, the inconsistent noise will be ignored immediately. On the other hand, increasing R means increasing the observation area and this is always true. With larger R, drones will explore the map and handle incorrect information faster. Therefore the total time they take to complete their tasks is shorter.

We also observe that although the distances between three testing ranges are the same which is four (from 5 to 9 and from 9 to 13) and the additional area covered in the second increase (from 9 to 13) is even larger, the decreased time in the second increase is smaller than what it is in the first increase. If R continues to grow, we predict that the decrease may eventually converge to a very small number near zero. This is reasonable because although both increases are at the same amount, the ratios of the additional covered area to the old area are different. When R increases from 5 to 9, there are a total of $9^2 - 5^2 = 56$pixels added which equals to 2.24 times 25 - the number of pixels covered by a square of R = 5. However, when R increases from 9 to 13, there are a total of $13^2 - 9^2 = 88$additional pixels added which equals to only 1.09 times 81 - the number of pixels covered by a square of R = 9. In addition, as R grows to a very large number, drones do not need to spend more time on searching and communicating, as every location will be known initially through observation. At this time, larger Rs will definitely provide the same information hence result in approximately the same completion time.

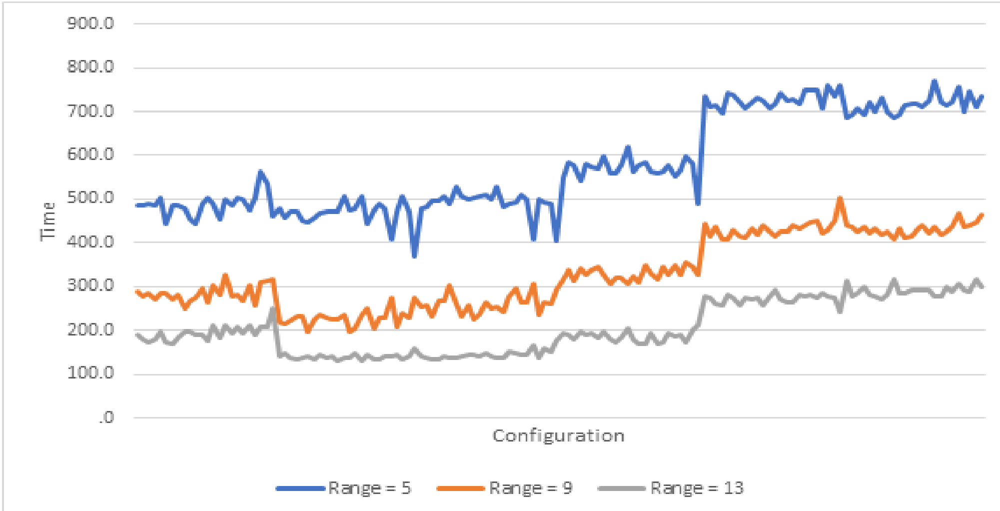


Figure 4: The time of completion for all configurations varying only R.

Hypothesis 2: *The level of noise N is directly proportional to the time it takes for all drones to complete their tasks because drones need to spend more time on correcting inaccurate information.*

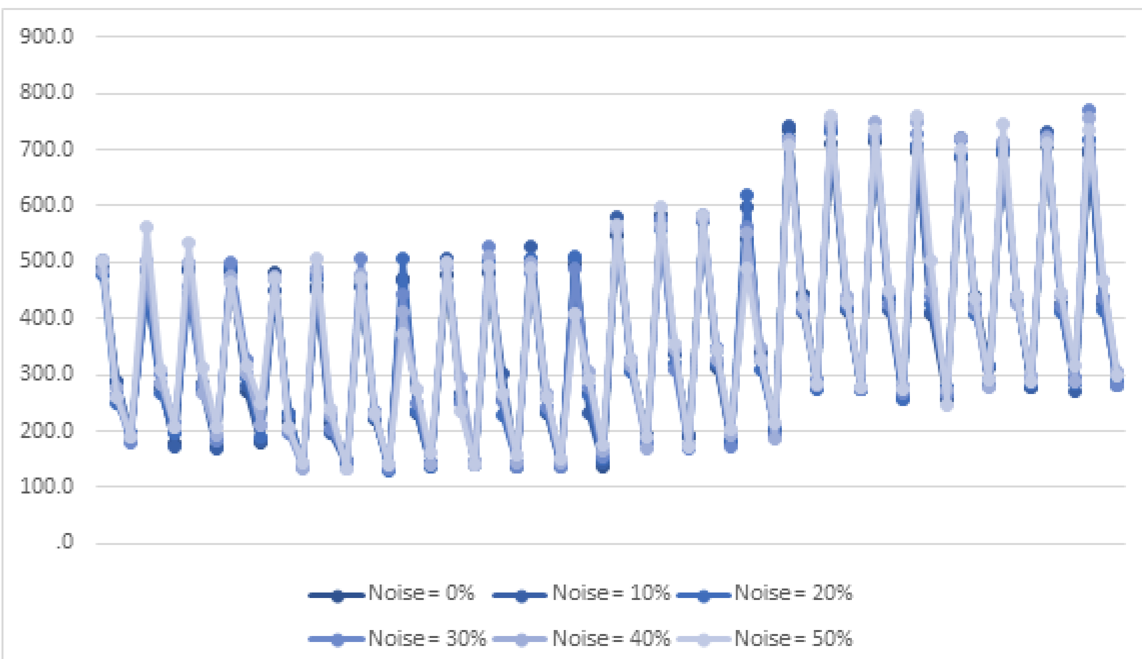
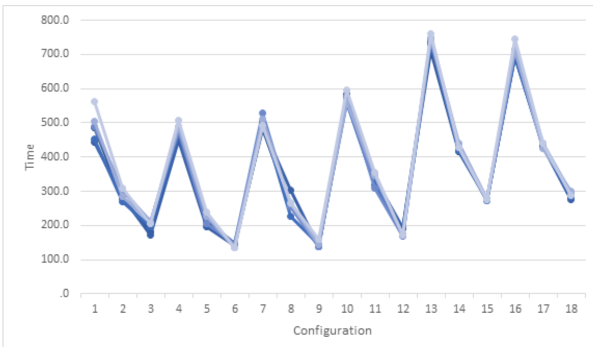
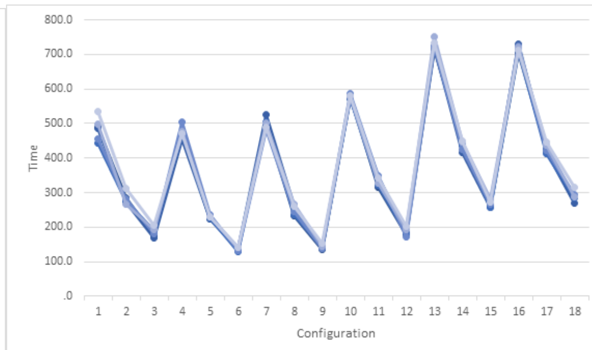


Figure 5: The time of completion for all configurations varying only N.

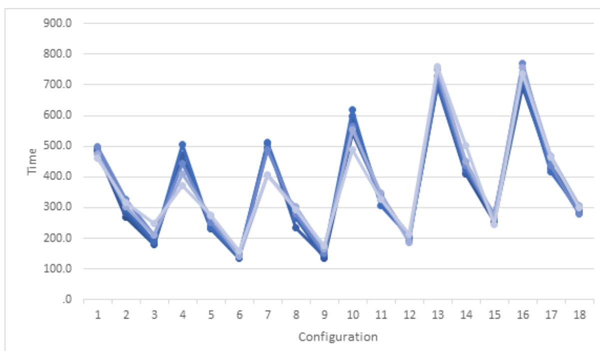
Except for the first sharing strategy, we assumed that more noise meant more troubles as drones had to suffer from inaccurate information. Figure 5 shows the time of completion for all configurations varying only the level of noise. However, because the differences between different levels of noise are not very clear, we decide to separate the data into smaller groups for easier analysis. Figure 6 displays the time of completion for all configurations varying only N - the level of noise in the experiments which are used to test Hypothesis 2. We group the results into three different groups separated by three sharing strategies. For each group, there are a total of 18 different configurations which can be divided again into six groups of three. Each group of three represents one configuration varying R - the edge of communication square. The decrease in time in each group of three is described above in the result of Hypothesis 1.



Sharing strategy (2)



Sharing strategy (3)



Sharing strategy (4)

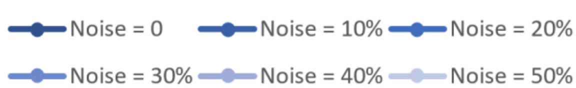


Figure 6: The time of completion for all configurations varying only N and grouped by sharing strategy.

We observe that using sharing strategies (2) and (3), the differences between six noise levels are not very clear (the average in differences is approximately 37 ticks). They are more clear while using sharing strategy (4) in which drones share everything that they have (the average is approximately 62 ticks). This implies that there may be some effects caused by the sharing strategies on the completion time which will be examined later in the result of experiments for testing Hypothesis 3. In overall, the level of noise does affect drones' completion time.

Detailed differences are shown in table 2. Most of the total configurations have increased completion time as we increase the noise level except for several cases. While using sharing strategies (2) and (3), as we increase the noise level from 0 to 10% or from 10% to 20%, the number of configurations having an increase in time is not much (approximately 50% of those configuration groups). However, as the noise level becomes larger (from 30% to 40% and 40% to 50%), the percentages start to increase more. Hence, for sharing strategies (2) and (3), a small increase (10% in this case) in high levels of noise may have larger effects than the same increase in lower levels of noise. The amount of information being shared may be responsible for this. In sharing strategies (2) and (3), drones have less information to share which will not be affected much by lower levels of randomly spawned noise. On the other hand, the results show an opposite thing for sharing strategy (4). As the level of noise increases, fewer configurations have an increase in time. Strategy (4) is more sensitive to the increases in lower levels of noise. If we increase the noise level from 0 to 10%, more than 50% of total configurations have an increase in time. Moreover, if we increase the noise level to 20%, that numbers are even larger. In this case, an increase in lower levels of noise has more effects. The reason could be, with an increase in noise level, there is a higher distribution of noise in the perceived region of drones which means that a larger portion of inaccurate information is corrected resulting in less time as compared to cases of lower distribution of noise in the perceived region. In overall, as we observed in the last column of table 2, most configurations experienced an increase in time when the noise level is increased from 0 to 50%.

Sharing strategy	Percentage of increase in time based on noise level					
	Diff(0, 10)	Diff(10, 20)	Diff(20, 30)	Diff(30, 40)	Diff(40, 50)	Diff(0, 50)
2	38.89%	50.00%	72.22%	66.67%	66.67%	88.89%
3	44.44%	55.56%	66.67%	61.11%	66.67%	94.44%
4	66.67%	77.78%	66.67%	50.00%	44.44%	66.67%

Table 2: Percentage of increase in time based on noise level.
E.g. the first percentage 38.89% means that while using sharing strategy (2) and increasing the noise level from 0 to 10%, there is 38.89% of the total number of configurations that have an increase in time.

Hypothesis 3: *At some levels of noise, the amount of information being shared might be proportional to the time it takes for all drones to complete their tasks. Because noise is applied on a percentage of the map being shared, the more information drones get from others, the longer they need to suffer from confusions.*

As mentioned above, the sharing strategies may have some effects on the completion time of drones to successfully replicate the drawing. Figure 7 displays the time of completion for all configurations varying the sharing strategies. The data structure is approximately the same as what we have in the experiments for Hypothesis 2. However, in this experiment, we group the results into six groups separated by six noise levels from 0 to 50%. For each group, again, there are a total of 18 different configurations.

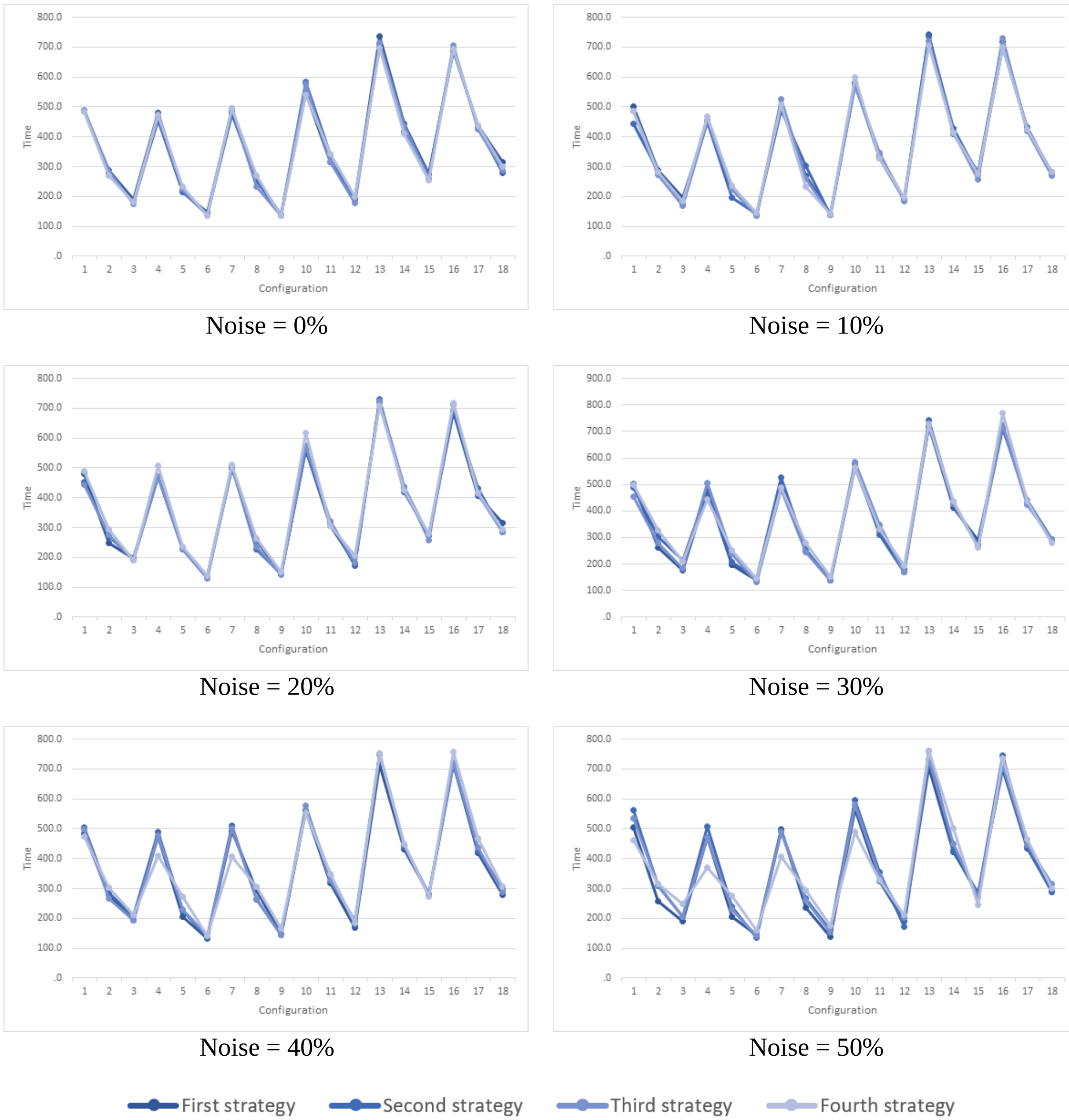


Figure 7: The time of completion for all configurations varying the sharing strategies.

We also observed that there are not many differences at low noise levels. As the noise level increases, the differences appear to be larger. Detailed differences are shown in table 3. Strategies (2) and (3) tend to belong to the same group because they do not show many differences in the results. Firstly, the percentages in Diff(2, 3) column imply that there is no significant difference between the increasing and decreasing time groups when changing between two strategies. Secondly, the percentages share the same trend as we compare strategies (2) and (3) with other strategies including (1) and (4). Comparing to strategy (1) in columns Diff(1, 2) and Diff(1, 3), it is clear that beginning at the noise level of 30%, more than 50% of the number of these configuration groups have an increase in time. Comparing to strategy (4) in columns Diff(2, 4) and Diff(3, 4), the noise level turning point is at only 10%. The reason could be the difference between strategies (2) and (3) which is the sharing of the connected portion of maps of drones. From results, we can assume that the probability of having connected portions of the map is less. Thus, in both strategies resulting map is similar.

For 0% of noise, all percentages are below 50% which implies that most of the configurations have a decrease in time as we change the sharing strategies in sequence from (1) to (4). Strategy (4) seems like the fastest as it supports more information to be communicated between drones. As observed above, strategies (2) and (3) show small differences. Strategy (1) tends to be the slowest because drones have to search for flags on their own. As the noise level increases, the percentages gradually become larger than 50% except for the case of strategies (2) and (3) in which there is not an absolute order for them. These increases show that the order is reversed which causes the first strategy to be the fastest while the fourth strategy becomes the slowest. The reason could be that strategy (1) is not affected by noise.

Noise (%)	Percentage of increase based on sharing strategy					
	Diff(1, 2)	Diff(2, 3)	Diff(3, 4)	Diff(1, 3)	Diff(2, 4)	Diff(1, 4)
0	33.33%	50.00%	44.44%	27.78%	50.00%	33.33%
10	33.33%	38.89%	61.11%	27.78%	66.67%	55.56%
20	44.44%	55.56%	83.33%	55.56%	72.22%	77.78%
30	66.67%	38.89%	72.22%	55.56%	50.00%	72.22%
40	77.78%	55.56%	66.67%	72.22%	72.22%	72.22%
50	72.22%	33.33%	61.11%	77.78%	55.56%	72.22%

Table 3: Percentage of increase based on sharing strategy.
E.g. the first percentage 33.33% means that while applying the noise level of 0 and using the second sharing strategy instead of the first one, there is 33.33% of the total number of configurations that have an increase in time.

Experiments for Hypothesis 1 has shown that the time will decrease if we increase the edge of the communication square regardless of the presence of noise. We observe from Figure 7 that although the time decreases as R increases, the relative rankings between four sharing strategies change, especially with the presence of high level of noise. In other words, with high levels of noise, four sharing strategies decrease by different amounts of time as we increase R. Figure 8 shows the decreases in time from six groups of configurations as we change R from 5 to 13. Each group consists of three configurations where the edge of communication square R is the only difference between them. Configurations in the first four groups use simple-structured drawings from group 1 while the last two groups use group 2's drawings. As the noise level increases, all sharing strategies, except for strategy (4), follow approximately the same trend. Strategy (4) which has a significant additional amount of sharing information compared to other strategies has a drop in the decreased time for the first four groups of configurations. This clearly implies that although with the same increase in the observation area, having more information to share in the environment where noise is applied at a high level will result in a decrease in performance comparing to other strategies.

Figure 8: The decreases in time from six groups of configurations as R is changed from 5 to 13.

6. Future Work

6.1 Effects from drawing structure

In the results for Hypothesis 1, it is worth noting that the decrease in time when increasing R is different between two groups of drawings. The gaps between lines in Figure 4 are larger for the last portion of the chart where the experiments were run on drawings from group 2. Table 4 shows the average decrease in time for both groups. As we increase R, the time it takes for all drones to complete drawings from group 2, which have more complex structures, decreases more than what it does for drawings from group 1. This implies that there may be some effects caused by the structure of the drawings.

Drawing group	Average decrease in time	
	when R increases from 5 to 9	when R increases from 9 to 13
1	227.9	109.6
2	290.4	150.4

Table 4: Average decrease in time when increasing R.

Besides, we observed in Figure 6 that by varying the amount of information being shared, the differences in the noise level becomes slightly more clear when strategy (4) is used for drawings in group 1 while there are fewer differences for drawings in group 2. Similarly, in Figure 7 by varying the noise level, we observe the same differences for drawings in group 1 and group 2. Moreover, in Figure 8, group 2 drawings follow a different trend in comparison to drawings from group 1 for all four strategies. Thus, these differences in trend between the two sets of drawings need to be further investigated.

6.2 The number of flags in the drawings

In future work, we can create more drawings in different sizes and use the data from all configurations which vary the size of the drawings to examine the role of K - the number of flags in the drawing - in the final result. Further, we can test the following hypothesis: K is inversely proportional to the time it takes for drones to complete their tasks. That is, the larger K is or the larger the drawing is, the faster the drones can replicate the drawing because they will spend less time wandering around looking for suitable flags.

6.3 Relationship between sharing strategy (2) and (3) while changing the noise level

In table 3, there is a pattern in column Diff(2, 3) which may be caused by some characteristics that make the system behave differently to two groups of noise levels: (1) 10, 30, 50, and (2) 0, 20, 40. We need to further investigate these two sets of noise level for several other drawings to test whether these two sets exhibit some difference in behavior.

6.4 Reliability of agent during map sharing

During communication, a drone can receive conflicting information about a pixel from multiple neighboring drones. In our case, we considered the information to be true if a majority of drones support it. However, this might not be efficient for cases where inaccurate information is spreading faster. Therefore, to increase the efficiency of the system, the reliability factor of each drone might be a good approach to consider.

7. Conclusions

Drone Self Assembly is an ideal setting in which multi-agent systems can be employed. It can be used to manage a swarm of autonomous intelligent drones for surveillance and patrolling in a particular set of areas by forming a closed structure or for demonstration purposes. It has very clearly defined agents (drones) each with their own goal (to occupy the flagged position). In this setting, each agent tries to maximize their performance concerning time and distance traveled by occupying the nearest available pixel. Each agent tries to avoid collisions and help other agents by sharing information for achieving their goal leading to global behavior that eventually converges.

Through our experiments, we measure the impact of environmental parameters like amount of information shared, the noise level in the shared information and communication range on the overall performance of the system. As anticipated, an increase in the edge of the communication square is inversely proportional to time which in our case is true for all configurations. An interesting observation to note that strategies (2) and (3) share approximately the same amount of information. As noted, R - the edge of the communication square - has stronger effects on the overall time but it might cost more to increase R in real life because there are more computations needed to handle and even more advanced hardware needed to be upgraded; therefore, causing implementation limitations. On the other hand, the total time can also be affected by varying the amount of information being shared. Future studies focusing on drawing's structure seem to be promising and could give useful results as there are significant differences between two groups of drawings. This system has a potential to work in real time scenarios after further investigation. Improvements still could be made, particularly in the agent design strategy. Overall, the system was successful in achieving the desired emergent behavior while maintaining autonomous behavior of agents.