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MASTER THESIS

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Disruption of movement or cohesion of groups through individuals

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and Mathematical Logic

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Firstly, I would like to thank my parents for letting me do my work when I needed to. Without them and their ongoing support I would not be able to make it this far in my studies.

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I declare that I carried out this master thesis independently, and only with the cited sources, literature and other professional sources.

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Abstrakt: Jen malé množství informovaných a stejně smýšlejících jedinců, *průvodců*, je potřeba k vedení jinak naivní skupiny. Zaměříme se na některé z možných změn, které mohou být způsobeny přítomností dalšího informovaného jedince s jinými zájmy, *narušitele*. Je naznačeno, že za normálních okolností není narušitel schopen způsobit nic významného. Abychom tomu předešli a zvýšili jeho šance na úspěch, zavádíme nový parametr — *důvěryhodnost*. Zkoumáme, jakým způsobem mění celkové chování. Ukazujeme, že zvýšená důvěryhodnost narušitele zvyšuje jeho vliv na ostatní. To poté způsobuje, že naivní jedinci jsou více ochotni jej následovat. Ukazujeme, že za vhodných podmínek se nakonec narušitel může stát tím, kdo vede skupinu.

Klíčová slova: multi-agentní systém, rojová inteligence, emergence, důvěryhodnost

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Abstract: Just a few of informed and like-minded individuals, *guides*, are needed to lead otherwise naive group. We look at some of the possible changes that can be caused by the presence of another informed individual with different intentions, an *intruder*. It is implied that he cannot cause anything significant under normal circumstances. To counter that and to increase his chances of success we intruduce a new parameter — *credibility*. We explore how it changes the overall behaviour. We show that by applying it to the intruder his influence over others increases. This in turn makes naive individuals more willing to follow him. We show that if the right conditions are met he can eventually become the one who leads the group.

Keywords: multi-agent system, swarm intelligence, emergence, credibility

Contents

Introduction

It is always interesting to see what group effort can bring forth. Even more so when there is no direct or continuous supervision. When everyone is just doing what they should or what is expected of them. Be it a swarm of insects, flock of birds, herd of animals, shoal of fish or just a work of nature itself. Whether it is about building some kind of a structure, moving towards a goal or solving a difficult problem. The results usually surprise upon successful completion or even during the progress.

Especially movement of these groups is quite a sight to behold. Moving as a single unit with a will of its own. Reacting to the environment and other outside disturbances. All the while taking into account individual needs and decisions of its members. There are usually no dedicated leaders. Instead the ones leading or controlling the whole group change over time based on current needs or other circumstances. Additionally, there is no rule saying that the ones in control have to be members of the group. On the contrary, their influence over the group might be much higher then that of regular members. Be it a predator that is about to feast on its prey, a herding dog keeping the herd in a designated area, or just some environmental obstacle. All of these things effectively affect the group's further actions. Some more than others but they are hardly ever ignored completely.

Affecting or disturbing the movement of groups using outside sources seems rather easy even without much research. They are just of higher priority to deal with than the need to check against others. Animals flee from predators and avoid obstacles as long as they feel that it will increase their chances of survival and safety. But can we do the same from inside the group? Can an individual, a member of a group, influence others in a similar way the outsiders do? Is it just a futile effort of said individual while in presence of others? The answer is not as clear because it depends on many factors. Things like presence of other influential individuals, conflicts of interest, outside disturbances, group size, overall spatial position in a group and many more parameters affect the outcome.

Before we can continue there is another issue. The question about the need to research these inside disturbances. Surely in a large enough group an effort of a single individual might not have much weight. It might be futile to even try to do something. Thinking about whole subgroups instead of individuals might be better in many cases. That is all true. But even one individual might be able to affect the whole group. We can see it as a "random error" in a system. Depending on the system it can be either insignificant or it can result in dire repercussions. Another way to look at it is whether its actions are intentional or unintentional.

Is it actively trying to sabotage the progress? Is it trying to guide the rest to the correct path? Or is it just some abnormality? An unfortunate mistake? There are many cases where doing things covertly and with caution is much better approach than letting everyone know about the circumstances. And in these cases we want to know our chances of success and how to improve them. Or contrary to that, how much freely can one act before the others take notice? There are many things to consider but even one individual has some power.

In our work we presume specific starting conditions. The group is made up of uninformed majority, informed minority and one individual with intentions different from others. The nature of their intentions with the group is not important here. It does not matter if they want the group to return to the corrent path or lure it to its doom. We simply observe how effective they are in their effort. Will they be swayed by others and abandon their goal? Will they give up and follow their own path? Will they succeed in persuading others? And to what extent if yes? These are the question we try to answer.

Earlier works suggest most of the answers to our questions. Informed minority can lead others [15, 30, 59]. Conflicts of interest can be resolved [12]. Uninformed individuals help with extremist opinions [16]. Therefore we are adding another parameter to the mix: social status, or *credibility* as we call it. Surely not all members of a group can be equal. There are bound to be some that are viewed differently for one reason or another. But will it really make a difference? That is another thing we are trying to find out.

There are many actions a group can perform when it acts according to swarming behaviour. Movement is just one of them. One that is easily observed and reproduced and that has been studied for some time now. Our work tries to shed some light on events when these "random errors" are concerned. Or at the very least confirm previous findings. Different environments require different compliance to the rules. This heavily influences the importance of "random errors". Distributed systems in general are designed to handle them. However there are still domains where even one such error might bring the whole system down. If we twist our views a little we can look at Game of Life [25]. When one of its cells behaves differently than others it might completely change the direction of the evolution depending on its location.

We study specific situations under specific conditions. In no way can we accomplish to find a general rule applicable to a wide variety of situations. But maybe we can at least point out a way for further research. Be it a path to follow or even one to avoid.

Example

This example is meant to make things a little more specific. There is default setting from which we start and then two different scenarios. Those describe how the herd can be disrupted by either outside or inside sources.

Default Setting: The Herd

There is a herd of sheep. Majority of its sheep are naive without any preference or not much interest to pursue their goal. Then there are some older sheep that know the way to the source of food and basically lead the rest. We ignore potential conflicts of interest and assume that they are already resolved. Therefore the whole herd goes towards one goal. The herd will most likely remain at the goal area when they arrive there. Additionally we assume that no individual sheep will leave the herd by itself under current conditions. That is, no fragmentation will occur.

First Scenario: The Predator

The herd moves as usual when suddenly a predator appears. It can be a wolf trying to prey on the sheep or a herding dog trying to keep the sheep in check. That is of no importance. The herd will flee away from the predator once it gets close enough. Or rather, the nearest sheep will react first once they notice the predator and the rest of the herd will follow.

In this case the predator is of higher priority than food. The predator becomes the one who controls the movement of a herd. Even if he does not actually lead the herd he still at least restricts its actions. The herd's normal movement is disrupted by the presence of the predator and in certain cases it may fragment into smaller groups.

Second Scenario: The Intruder

The herd moves as usual but somewhere inside it there is an intruder. It can be a sick or confused sheep that thinks that it is better to go another way. Or a sheep with more information about current environment and the knowledge of a better source of food. It can be a "wolf in sheep's hide" trying to lure others away and prey on them. Again, the intention of this intruder is of no importance. It does not matter it he wants to help the herd, bring it harm, or if it does not really care about the outcome. We just need to know that it is perceived by others as a regular member of the herd. A sheep like any other.

There are now more options that can occur. The intruder might be persuaded by others to follow them which is not desired. Or it can end up being ignored by others and break out of a group. The herd would in that case basically *return to default setting. Another possibility is changing the route while the goal remains the same. There is also a very small chance that it would take control of the herd. The last option is fragmentation of a herd when the intruder leaves the group with some sheep following it. All of these options are affected by many parameters of both the intruder and those of other sheep; like social status, zones of awareness, speed and more.*

The default setting or its variations were already studied so there would not be much benefit in studying it again. Although the first scenario is quite interesting there does not seem to be that much need to research it more. The usage of herding dogs or horses to control herds of cattle, sheep or other animals suggests at least basic understanding of this subject. The second scenario is the most interesting out of these options and not that thoroughly studied. It is the focus of our work.

Goals

Here we present three questions as our goals. We try to provide satisfactory answers to them through the results of this work.

1. **Can one individual take control over already guided group?**
   When there is a conflict of interest between two subgroups, even the smaller one can emerge victorious and lead the group. Is it true even if the smaller one contains only one individual? It might be so but the presence of naive individuals returns the favor to the informed majority. We try to either confirm this or at least expand upon current knowledge.

2. **When fragmentation occurs, is the intruder more prone to split alone or in a group?**
   In most circumstances, we want the group to remain cohesive without anyone splitting away from it. Not always is the result as we desire. When there is one individual attempting to achieve his own goals, fragmentation might become even more frequent. But how many will he take with himself if he manages to split from the group?

3. **How does higher social status of the intruder affect possible outcomes?**
   Being recognized by others as someone of higher importance and being more influential should change things up in some way. But is it enough to make a difference if just one individual is "special"? Does it still comply with swarm behaviour? We believe there was not much research done in regards

to social status. We examine the effects of its inclusion on the performance as a whole and when it is applied to previous goals.

Summary

This concludes the Introduction. Next follows Chapter 1 that covers related information; specifically topics and literature survey. It should provide basic understanding of the discipline. After that comes description of the model in Chapter 2. It delves deeper into its rules and goes into greater detail about our addition of credibility. Chapter 3 describes how we conducted our experiments; from the tools and specific phases to individuals parameters. Chapter 4 gives an overview of data representation and the results of each experiment phase. Finally, in Conclusion we discuss the results in relation to our goals and various possibilities for future work. After bibliography and lists of tables and figures come attachments. Attachment A provides a brief summary of our simulation tools. Attachment B contains additional graphs and tables of statistical data that would otherwise clutter the main text. The last one is Attachment C that contains the structure of accompanied DVD.

1. Background

The main theme of this thesis is swarm behaviour. While it is a part of artificial life as well as artificial intelligence, it is also largely related to biology. We should therefore explain some things first before going further with the core of our work. We also mention similar works in greater detail. Some of them were very helpful sources of inspiration for us.

1.1 Related Topics

In this section we give a brief overview of a few topics closely related to swarm behaviour. The first is swarm intelligence and some of its properties as it can be considered the main discipline of our work. Then the boids model which was the first computer simulation of swarm behaviour. Lastly artificial life and some notable simulators. There are other related topics which could provide further insight but these should suffice as an introduction.

1.1.1 Swarm Intelligence

> *"Swarm intelligence is the discipline that deals with natural and artificial systems composed of many individuals that coordinate using decentralized control and self-organization. In particular, the discipline focuses on the collective behaviors that result from the local interactions of the individuals with each other and with their environment."*

Marco Dorigo and Mauro Birattari, 2007 [19]

The expression was introduced by Gerardo Beni and Jing Wang in 1989 [4]. It is mainly inspired by biological systems. The individuals follow simple behavioral rules while locally interacting with others. Intelligent behaviour of the system then emerges as a result of these interactions. As a result, the system is capable of much more complex tasks than the individuals themselves.

Agent-Based Model

Swarm intelligence system is an example of agent-based model which is a subset of multi-agent systems. Each agent is an autonomous entity defined by its behavioral rules, parameters and local perception of the environment. Definition of a goal is optional and not always needed. Some of the properties of this model as described by Filippo Castiglione [6] include spatial landscape, evolution over time, and both discrete or continuous time and space. Agent-based models are also known as individual-based models.

There are many different tools available to use, like Breve [5], JADE [35], MASON [47], NetLogo [54], Repast [60], Swarm [65], and many more. Finding the most suitable tool might be difficult. Fortunately Robert Allan [1] and Cynthia Nikolai with Gregory Madey [55] made surveys to ease this process. In recent years, researchers started to take advantage of graphics processing units [22, 45]. This allows them to realize simulations of much larger scope while reducing its time complexity.

Emergence

Emergence is a concept of properties, functions, behaviours or patterns arising from interaction of a number of relatively simple entities. The arising systems are usually much more complex than the entities who created them. Emergence is interdisciplinary—being used as a principle in philosophy, science, art, religion, and others. It is viewed with small differencies in each of them. In swarm intelligence, it is closely related to self-organization. Various people came up with different definitions [13, 27] but the basic idea remains the same.

Nature itself is full of emergent structures and behaviours. For example, snowflake crystal patterns, termite mounds, ripple patterns in sand dunes or water, hurricanes, swarming of animals, inner working of ant colonies and many more.

Stigmergy

Stigmergy is one of the key concepts in the field of swarm intelligence. It is a form of self-organization, a mechanism of indirect coordination between agents. The principle is that actions of agents leave traces in the environment which then stimulates or reinforces the usage of subsequent actions. This leads to emergence of a seemingly systematic activity. It allows even extremely simple agents to collaborate and produce complex structures without any sort of planning or control.

The term was introduced by French biologist Pierre-Paul Grassé in 1959 who was studying termites [28]. It is derived from the Greek words *stigma* meaning “mark, sign” and *ergon* meaning “work, action”.

Algorithms

Swarming behaviour inspired the creation of many different algorithms, usually used for optimization as metaheuristics. They can be divided into two goups based on their approach. The Lagrangian approach is an agent-based model and works with individual agents. The Eulerian approach is a hydrodynamic approach modelling the oveall dynamics. It works with the density of the swarm.

Among the most well known are Ant Colony Optimization and Particle Swarm Optimization. Ant Colony Optimization was proposed by Marco Dorigo in 1992 [18]. The basic idea is finding the best path on a weighted graph. It was inspired by foraging behaviour of ants. Particle Swarm Optimization was developed by James Kennedy and Russell Eberheart in 1995 [37]. It is based on bird flocking behaviour. Particles representing solutions move in the search space towards the locally best particle. Other algorithms include for example Stochastic Diffusion Search [53], Self-Propelled Particles [67], Artificial Bee Colony Algorithm [36], Magnetic Optimization Algorithm [66], Krill Herd Algorithm [24] and more.

1.1.2 Boids

The boids model was developed by Craig Reynolds in 1986 [61]. It was originally meant as a new method to realize flock motion in computer animation as available alternatives were insufficient. In the basic flocking model boids follow three simple steering rules, also shown in figures 1.1a to 1.1c:

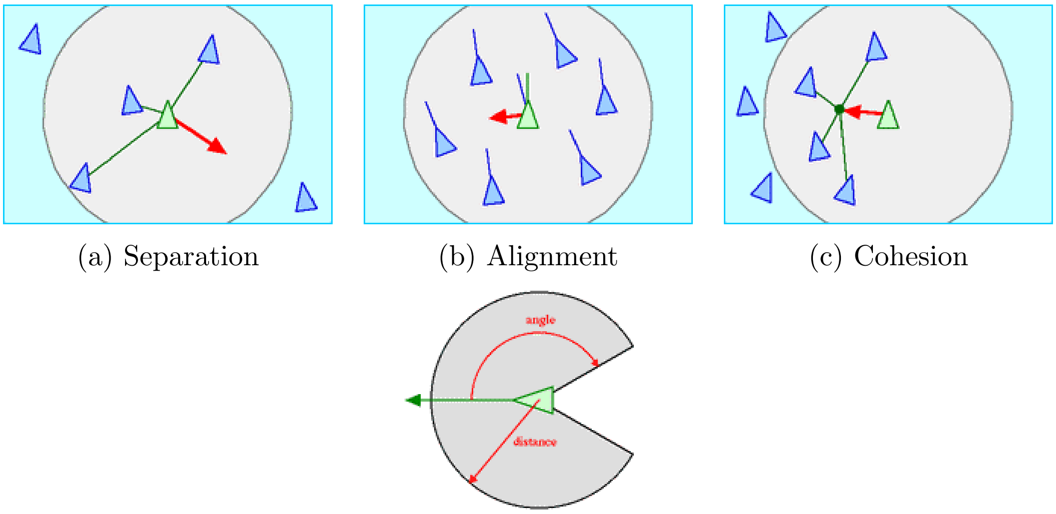
- *Separation:* Steer to avoid crowding local flockmates.
- *Alignment:* Steer towards the average heading of local flockmates.
- *Cohesion:* Steer to move towards the average position of local flockmates.

The resulting steering force is calculated as a weighted sum of all parts. Hierarchical approach is also possible. Additionally, each boid only percieves other boids that are in its neighbourhood which is defined by distance and angle, see figure 1.1d. There can be different neighbourhood for each of the basic steering rules. More steering behaviours mentioned by Reynolds [62] are listed in table 1.1.

Basic implementation of the boids model has an asymptotic complexity of $O(n^2)$ which becomes a problem for very large groups. It also goes against the nature of locality because everyone checks everyone else, not just those in vicinity. This problem can be solved by using spatial data structures or parallel simulation. Since its introduction, the boids model was used and extended in many simulations of swarm behaviour. The name boid comes from bird-like or bird-oid.

Behaviour	**Description**
Alignment	Steering towards the average heading of local flockmates.
Arrival	Same as Seek but slowing down to stop as it gets closer to the target.
Cohesion	Steering to move towards the average position of local flockmates.
Containment	Variation of Path following. Steering to remain within a certain region.
Evasion	Steering away from a moving target.
Flee	Steering away from a static target.
Flocking	Combination of Separation, Cohesion and Alignment.
Flow field following	Steering to align with a local tangent of a flow field.
Leader following	Steering to follow another moving individual while staying out of his way.
Obstacle avoidance	The ability to maneuver by dodging around obstacles.
Offset pursuit	Same as Pursuit but tries to pass near the target, not into it.
Path following	Steering along a predetermined path.
Pursuit	Steering towards a moving target.
Seek	Steering towards a static target.
Separation	Steering to avoid crowding local flockmates.
Unaligned collision avoidance	Keeping individuals from running into each other. Avoiding moving objects.
Wall following	Variation of Path following. Maintaining a certain offset from a "wall".
Wander	Random steering.

Table 1.1: Common steering behaviours.



(a) Separation (b) Alignment (c) Cohesion

(d) Neighbourhood

Figure 1.1: Basic steering rules and neighbourhood for boids. *Pictures taken from* `http://www.red3d.com/cwr/boids/`.

1.1.3 Artificial Life

> *"Artificial life is the study of artificial systems that exhibit behavior characteristic of natural living systems. It is the quest to explain life in any of its possible manifestations, without restriction to the particular examples that have evolved on earth. This includes biological and chemical experiments, computer simulations, and purely theoretical endeavors. Processes occurring on molecular, social, and evolutionary scales are subject to investigation. The ultimate goal is to extract the logical form of living systems."*
>
> *Christopher Langton, 1987 [41]*

Throughout history people were fascinated with the idea of artificial life and how to create it. There are more than a few examples in fiction, like Ovid's Pygmalion, Mary Shelley's Frankenstein, Carlo Collodi's Pinocchio, Rabbi Loew's Golem and many others. One of the first people closer to computer science to approach artificial life was John von Neumann who constructed the first self-replicating automata [68].

It was not until 1987 when Christopher Langton organized the first "Workshop on the Synthesis and Simulation of Living Systems", otherwise known as Artificial Life I, and in doing so helped in founding of artificial life as a discipline we know today. He was interested in the field even before this and continued with his involvement [39, 40, 42, 43]. There are three main approaches: soft from software, hard from hardware and wet from biochemistry. Artificial life is often abbreviated ALife or A-Life.

Game of Life

The Game of Life, or simply Life, is a cellular automaton and a zero-player game. It was invented in late 1960s by John Conway and published by Martin Gardner [25]. Since then it has attracted much interest in both scientific and amateur communities. It takes place on an infinite two dimensional grid of cells which can be *alive* or *dead*. Each cell has eight neighbours and its state is determined by a set of rules which are described in table 1.2. All cells are updated simultaneously at discrete time steps or generations starting from initial configuration called "seed".

There are many patterns with different complexity of behaviour. Among the basic ones are:

- *Still life:* stable with no changes
- *Oscillator:* repeats itself after a certain period
- *R-Pentomino:* studied extensively by Conway, does not end quickly but stabilizes
- *Glider:* moves across the environment
- *Glider gun:* grows indefinitely, generates gliders
- *Puffer train:* produces objects while moving

	Representation	**Rule**
1.	*death by under-population*	Any alive cell with fewer than two live neighbours dies.
2.	*sustainable life*	Any alive cell with two or three live neighbours remains alive.
3.	*death by over-population*	Any alive cell with more than three live neighbours dies.
4.	*birth*	Any dead cell with exactly three live neighbours becomes alive.

Table 1.2: Rules of the Game of Life and their representation.

Tierra

Tierra is a computer simulation developed by ecologist Thomas S. Ray in the early 1990s [58]. It simulates open-ended evolution of computer programs which compete for central processing unit time and memory access. The programs evolve through mutation, self-replication and recombination. Contrary to the conventional computer models of evolution there is no fitness function, only survival or death.

Ray used Tierra to explore basic processes of evolutionary and ecological dynamics. The results were more than successful as he could observe things like competitive exclusion and coexistence, host/parasite density dependent population regulation, the effect of parasites in enhancing community diversity, evolutionary arms race, punctuated equilibrium, and the role of chance and historical factors in evolution.

1.2 Other Works

Most of the works about swarming come from biology related fields. They focus on all sorts of its aspects. For example underlying mechanics [30, 44, 59], decision-making [9, 10], conflicts of interest [11, 12], and group size [29, 32], to name a few. Some works deal specifically with human crowds [21, 31, 46] or certain animals [2, 3, 38]. There are also lots of works that summarize others while adding their own thoughts or findings [14, 63, 69].

Apart from the focus of a work the next biggest difference between them is probably how their experiments and observations are conducted. The first option is to work with living creatures, be it fish, birds, ants, bees, or any other. This is usually limited to a specific species unless more of them are actually required. Depending on the goals and other circumstances we can either observe the creatures in their natural environment or under laboratory conditions. However, it is not always possible or desirable to use living creatures.

The second option is to use a model simulating certain behaviour. Even in this case there are lots of different possibilities and models to suit various needs. From simple spatial models to more complex underlying equations and mechanics. Most parameters are often set to reflect a certain species while others are observed to see what effect they have. As technology moves forward it allows for more robust and precise simulations. Together with the knowledge obtained from "natural" experiments the results only get more believable.

We selected a few works which we believe are closely related to our own. We give a brief summary containing information like basic goals, obtained results, and used methods. Each of them is listed under a theme that we think represents it well as a whole.

1.2.1 Informed Minority

In 2000, Stephan Reebs published a paper about foraging movements of fish schoals and the possibility of them being led by informed minority [59]. The important thing to note is that he used living fish for his experiments, specifically a schoal of 12 golden shiners, *Notemigonus crysoleucas*. He trained them to expect food at a specific time period of day in the same location. After that he combined the trained fish with naive ones in ratios of 5:7, 3:9, and 1:11 to observe the resulting behaviour.

The results were satisfactory. While naive-only shoals mainly remained in the "safe zone" and did not go towards the food the situation changed when at least one trained fish was present. The effect was stronger when the number of experienced fish was greater. Thus it showed that even small informed minority can lead the whole group.

1.2.2 Decision-Making

Further insight into leadership and decision-making was brought by Couzin at al. in 2005 [15]. They based their research around attributes that might affect the performance of group leadership. These included group size, number or proportion of informed individuals, transfer of information, and various additional knowledge, like who is informed or how good is one's information compared to others.

To show these things they used a simple spatial model. Each individual had two neighbourhoods, a smaller one for separation of higher priority and larger one for cohesion and alignment when there was no one to separate from. Informed ones had the knowledge of desired direction and a degree of assertiveness which determined their own preference over the one of their neighbours. There were some modifications for specific tasks when necessary, for example updating one's assertiveness depending on others.

They found out that only a small proportion of informed individuals is required to successfully guide a group. What is more, the larger the group the smaller the proportion of informed ones is needed. Furthermore, there does not have to be any explicit transfer of information between individuals for leadership to emerge. When there are more informed subsets with different preferences the result depends on their respective sizes and quality of their information. Overall this paper was very successful and it became one of the most cited sources in related fields of study.

1.2.3 Conflict of Interest

Although self-organizing groups can be led by their informed members there are bound to be cases when opinions differ and a consensus needs to be made. These conflicts of interest are the main focus of a paper by Conradt et al. from 2009 [12]. They used a spatial model based on Couzin's one [15] to determine how certain behavioral parameters affect the outcome.

The individuals were divided into two subgroups, where the majority was either big and contained about 80% of all individuals or it was small and had only one more member than the minority. Each of the subgroups prefered either of the two distinct targets in opposite directions. In other words, there was no uninformed individual. Additionally, members of the same subgroup shared behavioral parameters: movement speed, social attraction range, and degree of assertiveness. All of them could have one of three different values. The simulations were done for every combination of group size and parameter values.

First thing the results showed was that having additional knowledge, like parameter values of other subgroup, does not help much in accomplishing one's goal. Another one is that there is no sure way to get everything. There are trade-offs. While increasing one's own degree of assertivenes increases their leading rate it also increases fragmentation risk. The outcome is dependent on priorities of subgroups and their individuals but generally there are four different ones. Fragmentation and leading by majority are those that one would expect. Then there is leading according to "need" when the group is guided by those for which reaching their target is most crucial. The last one is leading according to "social indifference" when the group is guided by those for which group cohesion is least important.

1.2.4 From Naivety to Democracy

Informed individuals are able to guide a group. The ones with stronger desires might become leaders even if they are in minority and everyone else has an opinion of their own. However, what if there are some uninformed individuals? How do they affect the outcome? Do they affect it at all? It is probably a common thing to occur but up until 2011 there was not much research done in regards to it. Couzin et al. took it upon themselves to shed some light on these circumstances [16, 17].

To do so they used a variety of different approaches. The first was a spatial model based on the one they used in 2005 [15]. The second was an adaptive network model. It was inspired by voter model by Holley and Liggett [33] and built on a modeling approach proposed by Huepe et al. [34]. The third was a convention model based on a convention game described by Young [71]. The last one was an experiment with schooling fish for which golden shiners, *Notemigonus crysoleucas*, were used.

Once again they confirmed that informed minority is able to take control over informed majority if there are no other agents present. However with the presence of uninformed individuals the situation changed as the opinionated minority could no longer enforce their decisions on others. They showed that uninformed individuals help in acquiring equal representation of preferences and by doing so they promote democratic outcome.

2. Model

A properly defined model is needed before we can conduct any experiments. We introduce its basic features to get a general idea about it. We also mention how certain things work specifically in our case to not cause any misunderstandings. We then inspect movement rules in more detail. We should know what makes agents move the way they do. Finally, we explore credibility as it is an important addition to our work. We look at the reasons for using it and show how it is included in the model.

We implemented the model as part of our custom toolset called Muragatte [52] which is described in Attachment A.

2.1 Description

We use a spatial model based on Couzin et al.'s [15]. It has been used with some modifications in other works [12, 16] from which we also take inspiration. Moreover, it is easy to understand. Since it is tried out and proved to work we can focus on more important things in our research.

The behaviour of each agent is determined by movement rules. Although those are same for all agents there are still some differencies depending on current situation and the agents themselves. However, there is no direct communication between agents. They cannot tell which ones are informed and which are not. Or even what is their target. The only information they are able to obtain is current position and direction of their neighbours and only them. There is another parameter they have access to but more about it is mentioned later.

2.1.1 Modifications

We have made a few modifications to the model to suit our needs. The first minor one was the use of 2-dimensional space. By its definition the original model is suitable for both 2-dimensional and 3-dimensional space but we decided for fewer dimensions. There does not seem to be any negative effects in doing so. On the contrary, it made various things easier for us. With fewer dimensions we do not need as much time and space for our computations and the optional visualizations are more understandable.

The next set of changes is related to movement rules. Informed individuals in the original model have knowledge about the direction to the target. We however use target's position. It allows for better navigation of agents since they can locate their target from anywhere. Another minor change is that we explicitly define agent's behaviour when he has no neighbours. Uninformed ones just wander around. They walk randomly until they find a neighbour. Informed ones head straight to their target. The exact movement rules are detailed later.

The last notable change is the addition of social status, or *credibility* as we call it. It determines how much an agent influences others when the alignment steering rule is applied. In other words, the higher one's degree of credibility is the more strongly is his direction decision heard by his neighbours. We focus on it in more detail later in this chapter.

2.1.2 Basic Elements

We use various terms that should be quite familiar and already known. However there can be a lot of variations in their exact definition. Therefore, here we present their meaning in our model.

Neighbourhoods

Each agent has two neighbourhoods:

- **Zone of Attraction (ZOA)** It is defined by social attraction range ρ and angle of awareness β. Neighbours from this zone are used by steering rules of cohesion and alignment. Alternatively, we refer to it as *Field of View*.
- **Zone of Repulsion (ZOR)** It is defined by repulsion range α and angle of awareness β. Neighbours from this zone are used by steering rule of separation. Alternatively, we refer to it as *Personal Area*.

On all occasions $\rho > \alpha$ and $0° < \beta \leq 180°$. Figure 2.1 shows the relations.

Target

Target is an environmental objects or a place that informed agents might try to reach. It is defined by its position g of x–y coordinates. It can be either a point in space or a circular area of defined size. All targets are completely ignored by naive agents even if they have them in sight. Informed agents react only to their own target. Alternatively, we refer to it as *Goal*.

Agent

Agents are entities acting according to movement rules which are detailed later. They have a size of 1 body length which is the main measurement unit in the model. When in group, we generally divide them into three categories. *Naive*

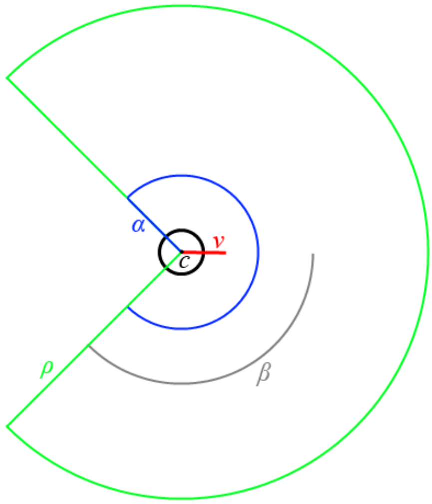


Figure 2.1: Agent's neigbourhoods

agents are uninformed. They do not recognize any target and cannot actively seek them. Unless they have at least one neighbour they just wander around. *Guides* are members of informed subgroup who share the same target. They form a majority of all informed agents. They should be the most likely to lead the group. *Intruders* are all other informed agents that do not share their target with guides. Apart from the rules the agents are defined by a couple of parameters which are summarized in Table 2.1.

Parameter	**Symbol**	**Description**
Position	c	The x–y coordinates.
Direction	v	Unit vector representing angle.
Speed	s	The distance one moves at each full step.
Degree of Assertiveness	ω	Preference of oneself over group.
Degree of Credibility	η	Social status, see Section 2.3.
Maximum Turning Angle	θ	How much can one turn at each full step.
Zone of Attraction	ZOA	See Neighbourhoods.
Zone of Repulsion	ZOR	See Neighbourhoods.
Target	g	Optional. The x–y coordinates of target if it is specified.

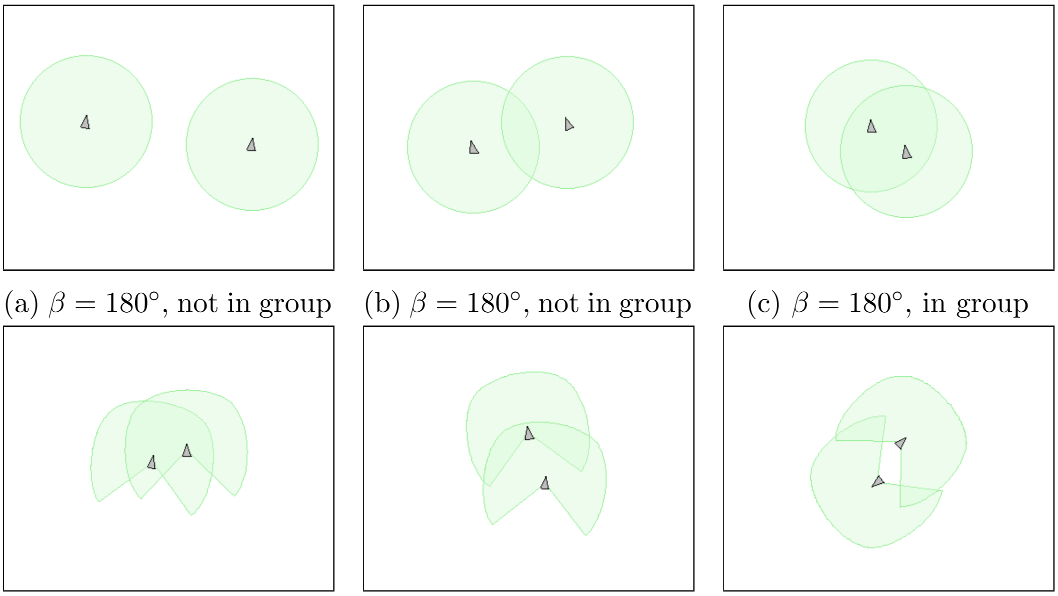
Table 2.1: Parameters defining an agent. The presence of an index, like c_i, denotes that the parameter value is for specific agent. Otherwise, the value is the same for all agents.

Group

Two agents are in a group as long as at least one of them is in the other's zone of attraction. By repeatedly applying this rule we get the whole group. When the agent's zone of attraction is full the agents always see each other. Otherwise, an agent might be part of a group even if he does not see anyone else. Figure 2.2 illustrates various cases.

Main group is a group with the most members, the biggest one. There can be only one main group at any time even if there are others that share the same highest number of members. The system decides which one of them it should be.

Stray agent is an agent that is not a member of any group.



(a) $\beta = 180°$, not in group (b) $\beta = 180°$, not in group (c) $\beta = 180°$, in group

(d) $\beta < 180°$, in group (e) $\beta < 180°$, in group (f) $\beta < 180°$, not in group

Figure 2.2: Grouping variants. (a) Agents are too far from each other. (b) Agents do not see each other even though their neighbourhoods intersect. (c),(d) Agents see each other. (e) One agent see the other one while he is not aware of him. (f) Agents do not see each other but they would if β was bigger.

2.2 Movement Rules

Movement rules make up the core of these kinds of models. They determine the behaviour of individual agents and therefore the whole system. We let them proceed in three stages. The first one is for *desired direction* which is based on current situation and the agents themselves. The second one is *adjusting* which is more or less the same for all agents. The third one is *movement* itself where the agents just move according to new values. Now follows a short informal summary of an agent's behaviour during each step. For the exact process see Figure 2.3.

For start, an agents checks for anyone too close so that he can get away from them. If there is no one like that he looks for other neighbours. If he has some he attempts to remain with them. Informed agents additionally combine it with their desire to reach their target. When they have no neighbours they either just randomly wander around in case they are uninformed or head straight to the target when they are informed. After this come adjustments due to environment, their own parameters, and noise. At last, the agent moves to a new position.

```
initialize d;
if anyone in ZOR_i then
    d ← KeepDistance(i) ;                         // See Equation (2.1)
else if anyone in ZOA_i then
    d ← Socialize(i) ;                            // See Equation (2.2b)
else
    d ← SeekOrWander(i) ;                         // See Equation (2.3)
end
d ← StayInArea(i, d) ;                            // See Equation (2.4)
d ← ProperTurn(i, d) ;                            // See Equation (2.5)
d ← ApplyNoise(i, d) ;                            // See Equation (2.6)
UpdateMovement(i, d) ;          // See Equations (2.7a) and (2.7b)
```

Figure 2.3: Updating an agent according to movement rules. Applies to specific agent i.

Desired Direction

Keeping Distance

The highest priority for all agents is to be separated far enough from others. When an agent i has any neighbours j in his zone of repulsion he will only think about getting away from them. Each agent tries to keep minimum distance α and up to angle β between himself and other agents. This behaviour remains the same whether the agent is informed or uninformed. If there are not any nearby neighbours the agent uses other means to determine his desired direction $d_i(t + \Delta t)$.

$$d_i(t + \Delta t) = -\sum_{j \neq i}^{ZOR_i} \frac{c_j(t) - c_i(t)}{|c_j(t) - c_i(t)|} \tag{2.1}$$

$j \in ZOR_i,\ j \neq i$ ... agent i not included

$c_k(t),\ k \in \{i, j\}$ ... position of agent k at time t

Socializing with Others

Not always will an agent have neighbours in zone of repulsion. In those cases he turns his attention to his zone of attraction with social attraction range ρ and angle of awareness β. His next action is dependent on his neighbours within it. First, he determines social component e_i which is a combination of cohesion and alignment towards his neighbours j. In the case of alignment, agent's own direction is also accounted for.

Uninformed agents use social component directly as their desired direction. On the other hand, informed ones weight it against their target in position g_i. Weighting is done through their degree of assertiveness ω_i. At 0 an agent completely ignores his target. At 1 an agent tries to find a compromise between the two. As it goes past 1 an agent is more in preference with reaching his target.

$$e_i(t + \Delta t) = \sum_{j \neq i}^{ZOA_i} \frac{c_j(t) - c_i(t)}{|c_j(t) - c_i(t)|} + \sum_{k}^{ZOA_i} v_k(t) \tag{2.2a}$$

$k \in ZOA_i$ ... both agent i and his neighbours j are included

$v_k(t)$ ... direction of agent k at time t

$$d_i(t + \Delta t) = \begin{cases} \dfrac{e_i(t + \Delta t)}{|e_i(t + \Delta t)|} + \omega_i \dfrac{g_i - c_i(t)}{|g_i - c_i(t)|} & \text{if informed} \\ e_i(t + \Delta t) & \text{if uninformed} \end{cases} \tag{2.2b}$$

ω_i ... degree of assertiveness of agent i

g_i ... position of agent i's target

Without Companions

When an agent has no neighbours in either of his zones his behaviour depends on his knowledge about target. Informed agents just go straight to their target since there is nothing else to disturb them. On the other hand, uninformed agents just wander around. That is done by applying a wandering component Π. It rotates their current direction by a sum of a random angle from uniform distribution, ranged $(-\theta\Delta t, \theta\Delta t)$, and a random angle from gaussian distribution, centered on 0, with standard deviation of $10°$.

$$d_i(t+\Delta t) = \begin{cases} \dfrac{g_i - c_i(t)}{|g_i - c_i(t)|} & \text{if informed} \\ v_i(t) + \Pi & \text{if uninformed} \end{cases} \tag{2.3}$$

Π ... wandering component, a random angle to rotate by

Final Adjustments

Containment

The first adjustment is to remain inside the operating space if the area is closed, like an aquarium. An agent tries to avoid the wall only when he faces it and is closer than ρ towards it. He does so by adding avoidance component $d_i^{\perp}$ to his desired direction. $d_i^{\perp}$ is a unit vector perpendicular to agent's desired direction $d_i(t+\Delta t)$ and opposite the wall.

$$\hat{d}_i(t+\Delta t) = \begin{cases} \dfrac{d_i(t+\Delta t)}{|d_i(t+\Delta t)|} + d_i^{\perp} & \text{if wall ahead and closer than } \rho \\ d_i(t+\Delta t) & \text{otherwise} \end{cases} \tag{2.4}$$

$d_i^{\perp}$ ... avoidance component, a perpendicular of $d_i(t+\Delta t)$

Turning

The second adjustment is to comply with one's own maximum turning angle $\theta\Delta t$. There is no change as long as the angle between current direction and desired one does not exceed $\theta\Delta t$. Otherwise, desired direction is taken as current direction rotated by $\theta\Delta t$ towards desired direction.

$$\bar{d}_i(t+\Delta t) = \begin{cases} \hat{d}_i(t+\Delta t) & \text{if } \angle\big(v_i(t), \hat{d}_i(t+\Delta t)\big) \le \theta\Delta t \\ v_i(t) \pm \theta\Delta t & \text{otherwise} \end{cases} \tag{2.5}$$

$\angle(a,b)$ ... angle between vectors a and b

$\theta\Delta t$ ... agent's maximum turning angle per time step Δt

Noise

The final adjustment is the addition of noise Σ which is done by rotating (adjusted) desired direction by a random angle. It is taken from a circular-wrapped gaussian distribution, centered on 0, with standard deviation $\sigma = 0.01$ radians.

$$d_i'(t+\Delta t) = \bar{d}_i(t+\Delta t) + \Sigma \tag{2.6}$$

Σ ... noise, small random angle to rotate by

Moving Forward

The last stage during a step is to update the agent according to newly obtained data. First we set new direction by normalizing a desired direction with adjustments. Then we can move the agent to his new position. Speed s_i and time step Δt determine how far will an agent move.

$$v_i(t+\Delta t) = \frac{d_i'(t+\Delta t)}{|d_i'(t+\Delta t)|} \tag{2.7a}$$

$$c_i(t+\Delta t) = c_i(t) + v_i(t+\Delta t)s_i\Delta t \tag{2.7b}$$

$s_i\Delta t$ ... speed of agent i per time step Δt

2.3 Credibility

Individuals differ from one another. No one is the same as someone else. Everyone is unique to some extent. Age, gender, experience, knowledge, impression; these are just a few attributes contributing to it. Even if we do not intend to or mean to we treat and react to each other differently. It should not be considered inherently as a bad thing but actually as something natural. It is one of the things that form relationships between individuals. What does all of this have to do with swarming behaviour? Actually a lot. At least if we consider natural groups.

For example, there is a large variety of individuals in migrating animals: large and small, young and old, male and female, children and parents, or even different species. In especially large groups, not all members would be related to each other. The opposite is much more probable. Animals with strong family ties would most likely stick to those of their own while keeping track with the group. Others might rely on their leader, an alpha male or female. Children would keep close to their parents. All kinds of different subgroups and their resulting relationships would be present.

This does not occur as much in artificial models because most models expect individuals to be virtually the same or with minimal differences. That is understandable as experiments are possibly easier to carry out and reproduce. Even in models that tackle with distinct subgroups there are usually only changes in basic attributes like speed or social attraction range. In other words, only existing attributes and parameters are changed. We do not deny their effect on the whole performance but we cannot consider it being related to relationships either. It does not really affect others as much or as directly as it could.

We use this opportunity to change that. In many relationships there is someone with an upper hand, someone superior to others. Credibility, charisma, authority, importance, seniority, social influence, social status, etc. There are many words and terms we can use to describe it but the general meaning stays the same. Influence over others. For the ones who follow it determines how much they can trust others and depend on them. For the ones who are followed it determines how much attention their decisions get. But how significant is its presence? To what extent does it affect the whole system? A research of its own would be necessary to cover it thoroughly. The focus and scope of our work does not allow us to do so. Our coverage is more of an introduction to the subject with some suggestions.

Of course, this is not exactly something completely new. Social influence is thoroughly researched in the field of social psychology. We can find many examples in there that encourage us to use credibility as a parameter with which to extend the model. Stanley Milgram showed in his experiment that people are susceptible to obedience in front of an authority figure [49]. Robert Cialdini defined six key principles of influence [7]: reciprocity, commitment and consistency, social proof, authority, liking, and scarcity. He and Noah Goldstein also contributed to the field of conformity [8]. Another related and interesting concept is minority influence which describes how majority can be affected to behave according to minority [51]. Although most of these works focus on humans it should still be applicable to other species as well. At least to some extent.

2.3.1 Reason for Extension

We should have at least a basic understanding about what credibility means for us. But why do we need it? Why are we extending our model with it? One of the main reasons was to bring something new to the research, to obtain new results. We did not want to just reproduce previous ones under the guise of a different purpose. That would be meaningless and counter-productive. So we looked at possible solutions to our little problem. We wanted something with explainable foundations that would make sense and be reasonable to include. Thus we came up with credibility.

We demonstrate our reasoning for this on two examples:

Example 1

Within a group G there are individuals A, B, and C. Individual A is generally regarded as a leader and the whole group counts on him. They will follow him no matter what. On the other hand individual B is basically a stranger who has just recently joined the group. Nobody trust him yet to give his choice much weight. Individual C is highly regarded by subgroup S. His influence over them is even higher than that of A's. Each of these individuals is trusted or respected on a different level. Now imagine that something unexpected happens. The reaction of the group should differ greatly depending on which one of them changes their behaviour first.

Example 2

A lesson at school is filled with various students and a teacher. Even though the teacher is an authority not all students will react the same way when he gives them an assignment to do. The studious ones would properly note it down with all the details. Others might take a brief note or take it into consideration. There might even be those who would outright ignore it because they just do not care. However our focus should be on those who did not pay any attention or misheard but still want to know what is going on. They should ask someone who can provide them with reliable information even though they would normally not interact with them. Close friends are useless if they did not pay attention either or if they like to fool us.

2.3.2 The Place in a Model

Being determined about the use of credibility and understanding what it stands for is only half way to solve the problem. There is still the issue of incorporating it into the model. There are many different ways to do so; some of which are discussed later. The final decision was quite easy to make due to our own restrictions. First, we wanted to keep it simple so that it does not feel intrusive in the model. Second, we already had a prototype implementation of the model that was working and we did not want to make huge changes to it. Overall, we wanted it to be easy to comprehend.

The degree of credibility η we ended up with affects how agents perceive the direction vector of their neighbours during alignment steering. Each agent has his own value that stays the same for the duration of simulation. It does not have any direct connection with cohesion of agents but it can still affect it. The degree of credibility basically puts the weight behind an agent's suggestion of what direction to take. Another solution would be necessary if direction vectors v were not guaranteed to be unit vectors.

The following equation replaces Equation (2.2a) from movement rules. In the alignment component the direction vectors v_j of all neighbours found in zone of attraction are multiplied by their respective degree of credibility η_j before being summed together. After that, a plain direction vector of current agent is added as well. Agents do not apply their own degree of credibility because it represents how they are perceived by others.

$$e_i(t + \Delta t) = \sum_{j \neq i}^{ZOA_i} \frac{c_j(t) - c_i(t)}{|c_j(t) - c_i(t)|} + \sum_{j \neq i}^{ZOA_i} \eta_j v_j(t) + v_i(t) \tag{2.8}$$

η_j ... degree of credibility of agent j

Default value for the degree of credibility is 1 with which it appears as if it was not applied at all. When the value grows from 1 up so should an agent's influence over others in relation to alignment. As it goes closer to 0 the agent's direction should be taken less and less into account and he should be completely ignored when it equals 0. Negative values should suggest taking the opposite direction. Please note that we were focusing on values greater or equal to 1. Values lesser than 1 were not tested or even used and their effect is mostly assumed based on equations.

2.3.3 Variety of Usage

The way we have used credibility and incorporated it into our model is just one of many. Surely it is not the only one. It might not even be the correct one since we based it more on our intuition than on proper scientific foundations. Therefore here we discuss what are some of the other possibilities, or rather properties, of credibility.

Global versus Local

Credibility is global when it is seen by everyone the same way. Whenever it is applied it is done under the same conditions no matter for which agents it is meant. This is also true in our case. It is easy to do and keep track of.

It is local when each agent might be regarded differently by other agents. For most he is just one of the lot, for a selected few he is a leader. Some might even ignore him. It is probably more closer to nature than the global approach. As an example, everyone in the group would depend on elders but children would depend even strongly on their parents.

Generally, we can call it familiarity. It more clearly represents additional ties between individual agents and subgroups.

Static versus Dynamic

With static approach the credibility is applied in the same manner at all times during a simulation. In the most trivial case it might be just a numerical value like in our model. In other cases it might depend on the agent that is asking.

The approach is dynamic when the degree of credibility changes over time or depending on various circumstances. It might be based on number of following agents, succeeding or failing in reaching a goal, providing valuable information, and so on. It might get really complex. The main restriction we have here is the model we use and what it allows us to do.

With some stretch we can also call static and dynamic approaches long-term and short-term respectivelly.

3. Experiments

All of the experiments were done in our custom simulation toolset Muragatte [52] which is more covered in Attachment A. It was run on Windows 7 Professional with Service Pack 1 on ASUS F3JP notebook (Core2Duo processor @ 1.83 GHz, 2 GB). In this chapter, we discuss values of various parameters and the structure of our experiments.

3.1 Parameter Space

Parameters can be divided into two groups. The first group defines experiments in general. They are the same for all experiments. The second group is composed of parameters we observe. They are different based on concrete experiment. We need to set values for both the defining ones and the observed ones. Most of these values are based on earlier works [12, 15, 16]. However, not all of them are directly copied. We made minor changes or decided on our own values when we felt it was necessary. There are also new parameters in our model and their values had to be somehow set as well. Our specific decisions are discussed in their respective sections. Additionally, we also define values of parameters that were used by our toolset to initialize and run the experiments.

3.1.1 General Setting

Starting Conditions

All experiments are performed in the same closed area of width 200 and height 150. There are two targets, a primary one for guides and a secondary one for intruder, both of which are circles with diameter of 5. They return uniformly distributed random position from inside of them when it is requested. All agents start at uniformly distributed random position inside a spawning area which is a square of size 3. They start with uniformly distributed random direction covering the full range of $\langle -180°, 180° \rangle$. Figure 3.1 further details the structure.

Length

Each experiment was run for 2500 steps with 200 replications and time per step $\Delta t = 0.1$. More replications would be difficult to do due to hardware limitations.

Figure 3.1: Environmental area used in experiments

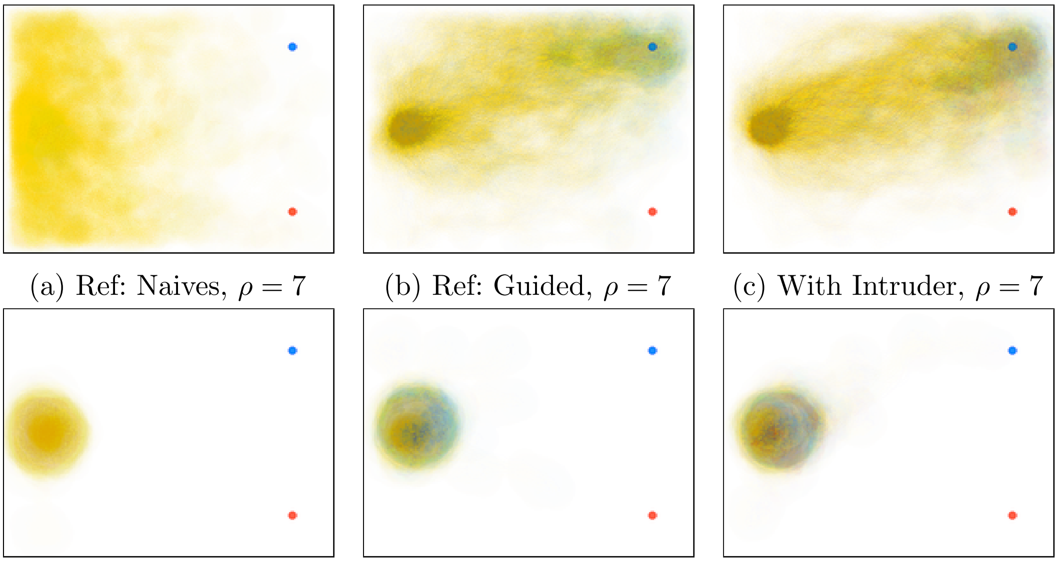
Counts

Group sizes were multiples of 10 in the range from 10 to 100. There were always 5 guide agents and 1 intruder agent. An exception to this are reference experiments in which there was no intruder or even no guides. Table 3.4 shows all the cases.

3.1.2 Agent Setting

Shared

All agents regardless of their type have speed $s = 1$, turning angle $\theta = 115°$, angle of awareness $\beta = 180°$, repulsion range $\alpha = 1.5$ and social attraction range $\rho = 7$. *Please note that the distance from one agent to another element, be it also an agent or a target, is measured from the center of the one asking to the bounding circle of the other element.* In the case of repulsion range it means that agents try to maintain a free space of minimum distance $\alpha' = 1$ between themselves. We slightly increased the value of social attraction range ρ from the one used in other works [15, 16] to decrease number of fragmentations. We did not use higher values because they produced undesirable behaviour which is illustrated in Figure 3.2.



(a) Ref: Naives, $\rho = 7$ (b) Ref: Guided, $\rho = 7$ (c) With Intruder, $\rho = 7$

(d) Ref: Naives, $\rho = 10$ (e) Ref: Guided, $\rho = 10$ (f) With Intruder, $\rho = 10$

Figure 3.2: Inappropriate behaviour with high social attraction range ρ for $N = 50$. Intruder's parameters in (c) and (f) are $\omega = 0.5$ and $\eta = 1$. (a)–(c) shows ρ as it was used in experiments. (d)–(f) shows faulty behaviour when ρ is increased. The whole group remains in a *stable* state and does not really move even if there are informed individuals. This behaviour was the same for other group sizes except for $N = 10$, $N = 20$ and partially $N = 30$.

Specific

Degree of assertiveness ω, degree of credibility η and target are dependent on agent type. Table 3.1 gives a summary of those values. Experiments were done for all combinations of intruder's assertiveness and credibility. The values of credibility were based on following assumptions:

- $\eta_{\text{normal}} = 1$ base value
- $\eta_{\text{high}} = 2$ slightly higher than normal but not by much
- $\eta_{\text{very\_high}} = 5$ should rival guides in influence
- $\eta_{\text{extra\_high}} = 20$ much higher than guides

Type	**Assertiveness ω**	**Credibility η**	**Target**
Naive	0.1	1	—
Guide	0.5	1	Primary
Intruder	{0.5, 1, 3}	{1, 2, 5, 20}	Secondary

Table 3.1: Agent specific parameters

3.1.3 Application Setting

Seeds

It is important to get results out of experiments but it is even more important to be able to reproduce them. Defining a specific seed value is necessary for that when using randomization of any sort. Our simulation tool runs batches of experiments based on group size so we only needed ten of them. The exact seed value for each group size is shown in Table 3.2.

N	**Seed**	**N**	**Seed**
10	120130207	60	620130208
20	220130207	70	720130208
30	320130207	80	820130208
40	420130207	90	920130209
50	520130207	100	1020130209

Table 3.2: Seeds used in experiments

The Rest

Table 3.3 summarizes other setting for the application. The definition of scene, species, and styles were loaded from their respective files that were provided.

Experiment		**Output**	
Runs	200	*Save History*	No
Length	2500	*Take Snapshots*	Yes
FOV Range	7	*Snapshot Scale*	5
FOV Angle	180	*Snapshot Alpha*	32

Table 3.3: Summary of used MuragatteThesis setting. Parameters are listed as they appear in the application.

3.2 Progress

We divide all the experiments into a few types or stages as we go through them towards our goals. They differ in group composition, as is shown in Table 3.4, and some parameter values. The whole structure is as follows:

1. **Reference** These experiments consist of two subtypes: *Naives* and *Guided*. Both of them are without any intruders. In this sense they are sort of a starting point and the basic source to compare against. They were also

used to determine whether groups behave as they should when parameter values were being set. Figure 3.2 provides an example of this.

(a) *Naives* A trivial case with only naive individuals. It is expected that they remain mostly cohesive and move randomly inside the area.

(b) *Guided* Some of the naive individuals are replaced with guides. Apart from cohesion the group is expected to move towards the guides' target instead of moving randomly.

2. **No Credibility** There is an intruder instead of one naive individual. Credibility is set to $\eta_{\text{normal}} = 1$ for all individuals which makes it the same as if it would not be used at all. Only intruder's degree of assertiveness changes its value to $\omega_{\text{medium}} = 0.5$, $\omega_{\text{high}} = 1$, and $\omega_{\text{very\_high}} = 3$. To some extent this is also partially a reference for further experiments because previous works [12, 15, 16] suggest either minimal disruption by intruder for lower degrees of assertiveness or their splitting from group at higher levels.

3. **With Credibility** These are the main portion of our experiments that utilize the addition of credibility into the model. There are the same conditions as before but now even intruder's degree of credibility goes through different values. It is gradually increased from $\eta_{\text{normal}} = 1$ to $\eta_{\text{high}} = 2$, $\eta_{\text{very\_high}} = 5$, and $\eta_{\text{extra\_high}} = 20$. We expect to see some changes when compared to previous cases. Both in regards to how a group fragments and towards which target it moves.

Overall there are 12 sets of experiments per group size which makes it 120 experiment sets in total.

Type	**# of Guides**	**# of Intruders**	**# of Naives**
Ref:Naives	0	0	N
Ref:Guided	5	0	$N-5$
Normal	5	1	$N-6$
$N \in \{10, 20, 30, 40, 50, 60, 70, 80, 90, 100\}$			

Table 3.4: Group composition for various experiments. *Normal* ones cover cases both with and without credibility.

4. Results

All data that we got from experiments were processed using R v2.15.0 [56]. It was used to create all the various graphs and to compute other statistical values found in Attachment B. Visualizations such as the ones from Figure 3.2 were produced by our tools. The original output data and all visualizations in higher resolution are available on accompanied DVD [64]. The important thing to note is that the results capture only the end state of simulations. Anything that happened during its run is ignored. Naming conventions are covered by Table 4.1.

MTE_*s*_*n*-*g*-*iac*

s ... total number of agents
n ... number of naive agents
g ... number of guides
i ... number of intruders
a ... intruder's assertiveness
c ... intruder's credibility

$$a = \begin{cases} & \text{if } i = 0 \\ \text{M} & \omega = 0.5 \\ \text{H} & \omega = 1 \\ \text{V} & \omega = 3 \end{cases} \qquad c = \begin{cases} & \text{if } i = 0 \\ \text{N} & \eta = 1 \\ \text{H} & \eta = 2 \\ \text{V} & \eta = 5 \\ \text{X} & \eta = 20 \end{cases}$$

Table 4.1: Naming conventions for visualizations and experiments. For example *MTE_40_35-5-0* applies for guided reference of size 40 and *MTE_70_64-5-1MV* applies for regular experiment of size 70 with $\omega = 0.5$ and $\eta = 5$.

4.1 Data Representation

This section is meant to give an overview of how to interpret our specific data representations. Some processing of original output data is required in most of them so we go through that briefly as well.

Fragmentation

We divide fragmentation into three cases. The first one is for general situations when there is more than one group or at least one stray agent. The second one is for situations when the intruder ends up being alone as a stray agent. The third and last option is for situations when there is more than one group and the intruder is part of any of them. However, it does not account for any stray naive agents or guides. The first option is usually a sum of the other two and it is also the only one used for reference experiments. Each run of all experiments receive one logical value for each of these cases. These values are then used for further statistical computations. Unfortunately, with our tools we cannot further specify when the fragmentation occured. There is a major difference between breaking up anytime halfway through and right after start when the group is stabilizing.

Target Distance

For this we take the minimum distance between the main group and the targets based on experiment type. Both targets are considered for experiments with the intruder while only primary target is considered for guided reference experiments. It is skipped for naives reference type. Just like with fragmentation we do not work with the distances themselves but create new logical values based on them. For each target we consider two states: *at* and *near*. A group is *at* target when at least one of its members has it at least partially in their field of view. A group is *near* target if it is not *at* target, the minimum distance to it is less than the minimum distance to the other target and less than half the distance between both targets. To include some information about the intruder himself, table B.11 covers minimum, median, and maximum of absolute distances between him and his target. Again, only the end state is taken into account. We do not know if a group reached its prefered target but left it in the remaining time.

Intruder Group Size

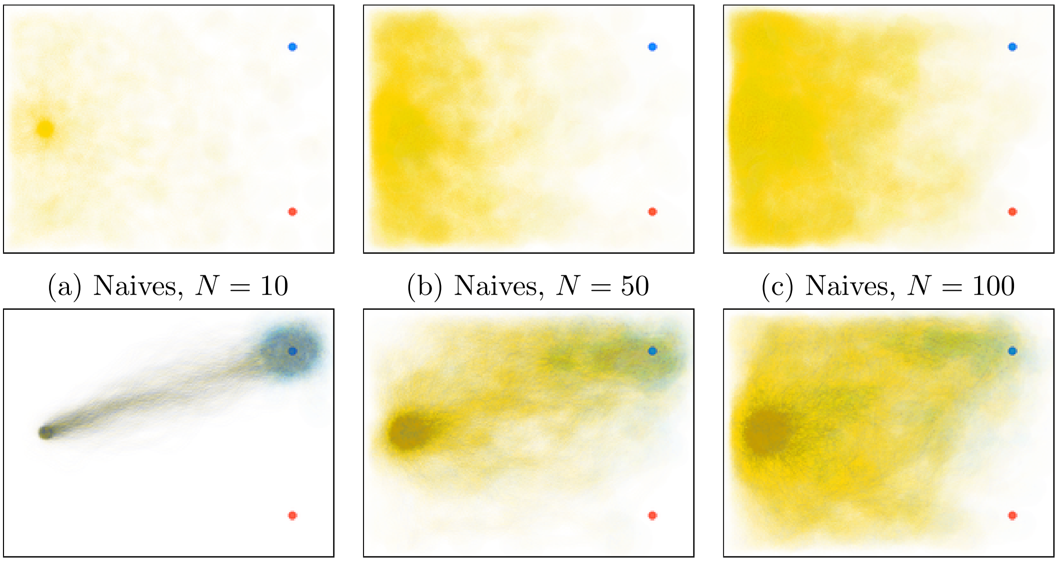
There are three cases of interest regarding group size when the intruder is present. The first one is when no fragmentation occurs and the group remains cohesive. The second one is when the intruder ends up alone while ignoring any other groups and stray agents. The third one is when fragmentation occurs and the intruder is part of any group. Among them, the last one deserves to be inspected further because the size of said group might differ greatly. We show the distribution of these sizes aggregated by 10% for each total group size in Figures B.3 to B.12. They are accompanied by tables showing the data for other cases as well. We should note that all of the results related to this are only in Attachment B and the main text contains none of it.

Layered Visualizations

Also refered to as layered snapshots, these images are supposed to show the end state of groups and their movement up to that point. Everything takes place inside the environmental area that is shown in Figure 3.1. It is a compilation of snapshots of individual runs where each layer is applied unto the others with some transparency level. This helps in highlighting frequently taken paths or positions. Each agent is visualized at his end position with his zone of attraction and a track of his movement from start to end. Naive agents are yellow, guides are blue, and intruders are red.

4.2 Reference

Both naive and guided groups serve as a good starting point for further experiments. They provide us with default behaviours against which to compare the rest. Figures 4.1a to 4.1c show how naive groups move randomly through the area. There does not seem to be much change when the group size increases. On the other hand, from Figures 4.1d to 4.1f we can see that the group is actually led towards the target. Contrary to naive groups the number of individuals does matter. As it increases the group takes more detours and loses its focus.



(a) Naives, $N = 10$ (b) Naives, $N = 50$ (c) Naives, $N = 100$

(d) Guided, $N = 10$ (e) Guided, $N = 50$ (f) Guided, $N = 100$

Figure 4.1: Layered visualization: naives & guided

Although visualizations might be pleasant to the eyes while giving a rough idea about the group's movement they cannot provide any more information. That is even more true when there are layers upon layers and the individual cases are impossible to tell apart. From Figure 4.2 we can see that groups fragment more frequently as their size increases. There is no fragmentation for low enough numbers, like $N = 10$ and $N = 20$, but as the size grows so does the chance for it to happen. It tops at 33% for naive group at size $N = 100$. The presence of guides does not make it much different. In fact, the proportion of guided groups that split is slightly lower in most cases even if it is almost insignificant.

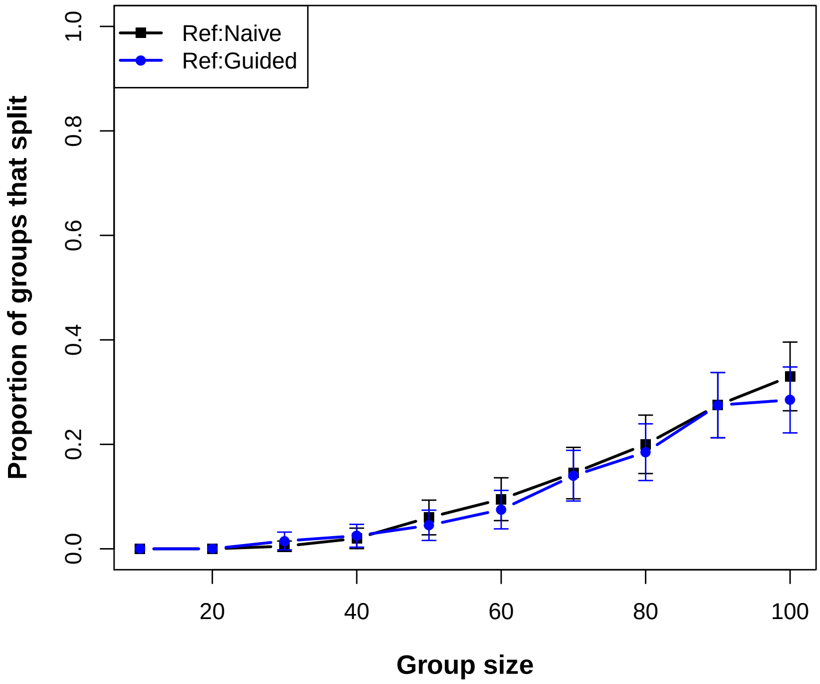


Figure 4.2: Fragmentation of naive and guided groups

We do not take naive groups into account for distance from targets because they just wander around without any specific goal. There is no drive for them to reach it and it is more of a coincidance when it actually happens. However, guided groups are different. We expect them to move towards the target and they do so with more or less difficulties. With the group increasing in size the proportion of groups that reached the target and even those who got near enough decreases as can be seen in Figure 4.3. We suspect two things to be the main cause of this. The first is fragmentation because we only check for status of the main group. It is possible for the main group to have no guides after splitting and therefore not going towards the target. The second case is the number of guides which remains the same for all sizes. They might have more difficulty in persuading naive individuals as their numbers increase.

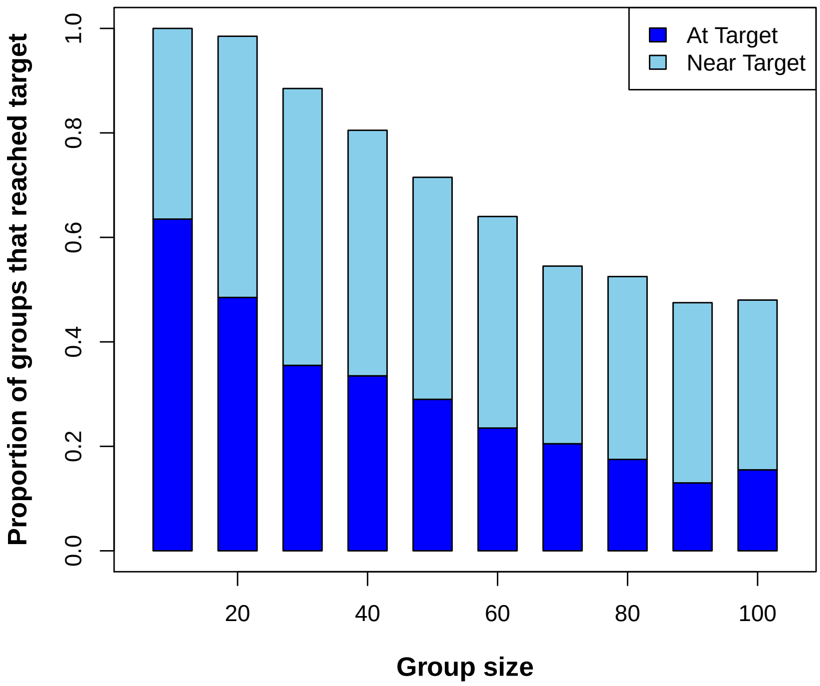
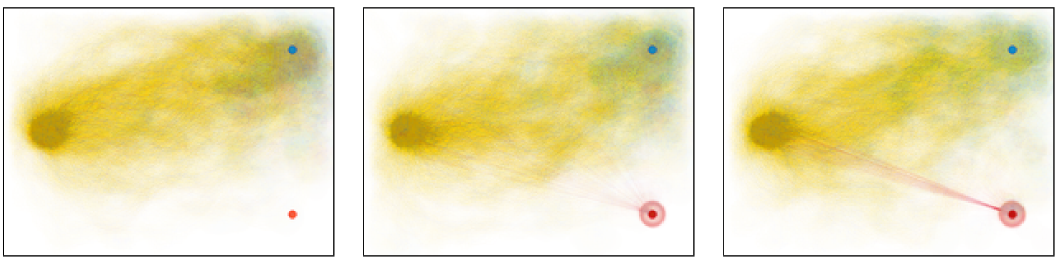


Figure 4.3: Guided groups reaching their target

4.3 No Credibility

Things become a little more interesting when the intruder is present. At this stage we leave his degree of credibility η at its default value and change his degree of assertiveness ω instead. By comparing Figure 4.4a to Figure 4.1e we can see that the movement became less spread out and more focused while the intruder remains with the group. At higher levels of assertiveness the overall movement does not change much but the intruder leaves the group by himself. He does so either throughout the course of the simulation or close to the start as is apparent from Figures 4.4b and 4.4c respectively. Similar behaviour was observed for other group sizes as well.



(a) $\omega = 0.5$ (b) $\omega = 1$ (c) $\omega = 3$

Figure 4.4: Layered visualization: assertiveness. $N = 50$, $\eta = 1$

Further inspection of fragmentation reveals quite interesting results. With inconsiderable exceptions there is basically no case of the intruder splitting alone when his degree of assertiveness is at medium level. The situation completely changes when we increase it to high level. Most fragmentations are the result of the intruder splitting alone away from the group in what makes 63.5% at lowest for $N = 90$ and 79% at highest for $N = 10$. On the other hand, the intruder splits with a group even less than both references for sizes $N \geq 50$ and a little more than them for lower sizes. Both of these cases are covered by Figure 4.5 on left and right respectively. Very high level is similar to high one in shape with both types of intruder's fragmentation being a little more frequent. For details see Figure B.1.

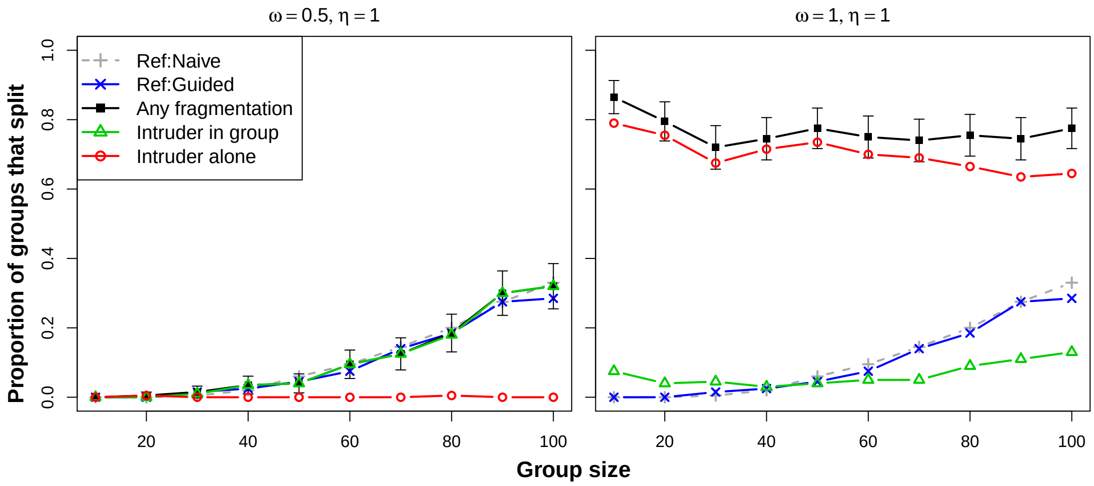


Figure 4.5: Changes in fragmentation based on assertiveness

With the inclusion of intruder the group now has two options where to go. However it does not seem to change much in comparison with guided reference. It manages to reach the primary target a little more frequently but it is not by much. Although the group gets near the secondary target a few times it is not anything major. It does not even affect the primary one. One of the reasons might be that the intruder actually is not part of the group most of the time. Figure 4.6 shows only the case with high degree of assertiveness because the differences in the other two levels are not significant enough. For details see Figure B.2.

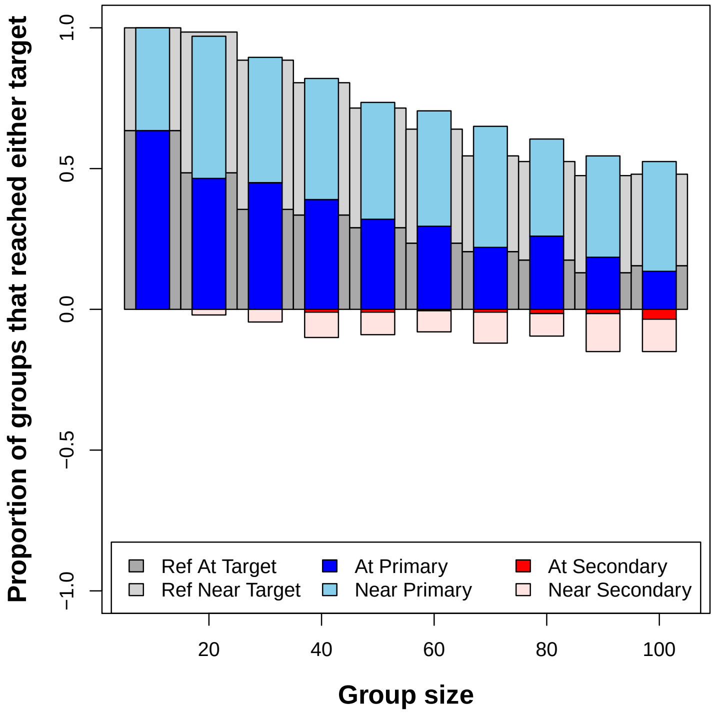
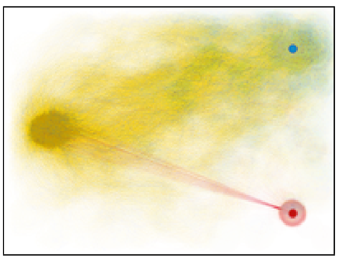


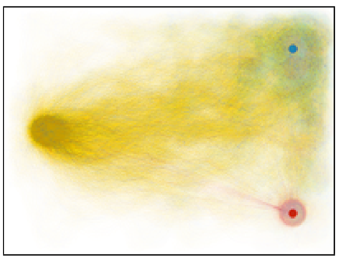
Figure 4.6: Reaching targets with an intruder. $\omega = 1$, $\eta = 1$

4.4 With Credibility

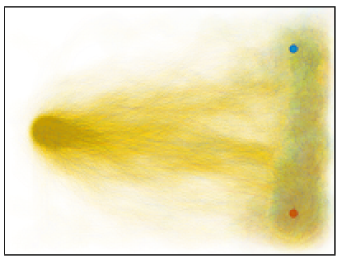
Finally, we get to the main part of the experiments when credibility is included as well. Leaving it at default value and changing only assertiveness determined mainly if and when the intruder leaves the group. But the more we raise it the more group members are willing to follow him. The intruder's increased influence over others starts to show. This is especially visible for higher degrees of assertiveness. From comparison between Figures 4.7a and 4.7b we can see that the route towards primary target is not as straightforward as it used to be when the intruder's influence rivals that of guides. Additionally, individuals start to sway towards the secondary target. It is even better when the intruder is at his best in Figure 4.7c. At this point he actually manages to take control a fair number of times as the secondary target seems to be prefered.



(a) $\eta = 1$



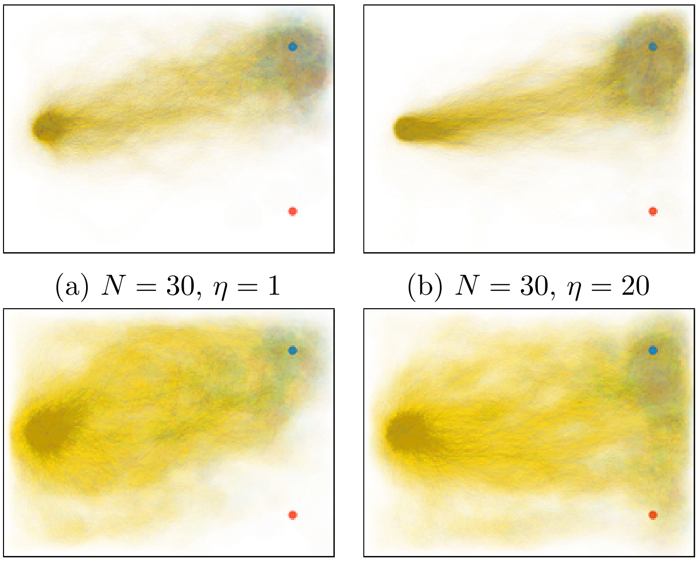
(b) $\eta = 5$



(c) $\eta = 20$

Figure 4.7: Layered visualization: credibility in general. $N = 50$, $\omega = 3$

Other behaviours worth mentioning were observed for medium degree of assertiveness. For lower group sizes of $N \leq 30$ the increasing degree of credibility stabilized the whole group. It became less spread out and more focused. However that was not the case when the group size grew bigger. The intruder no longer supported the guides and attempted to take control instead. A sample of these behaviours is captured by Figure 4.8.



(a) $N = 30$, $\eta = 1$ (b) $N = 30$, $\eta = 20$

(c) $N = 80$, $\eta = 1$ (d) $N = 80$, $\eta = 20$

Figure 4.8: Layered visualization: credibility at medium assertiveness. $\omega = 0.5$

It is not as apparent from visualizations alone but degree of credibility changes the way the intruder splits away from the group. In Figure 4.9 we can see a nice transition of his behaviour from default value to the highest. At a default normal value of $\eta = 1$ the intruder mostly ends up as a stray agent while being in group in only a few cases. With increasing credibility he has a company more frequently and spends less time alone. At the highest degree of credibility $\eta = 20$ he even stops splitting alone when the group is big enough. There is still more to observe in relation to group size. We can see that fragmentation rate decreases for group sizes up to $N = 40$ and then it mainly increases slowly. Other than that Figures B.3 to B.12 show that the distribution of the size of intruder's company after fragmentation gradually more and more resembles Gaussian curve.

But not only size matters. Looking at the overall picture in Figure B.1 we can see that degree of assertiveness is just as important in determing credibility's effect. With medium degree of assertiveness there is almost no sign of intruder ending up alone. Even splitting with others mostly resembles reference groups for all degrees of credibility except for the highest one. This is in complete contrast to cases with higher assertiveness.

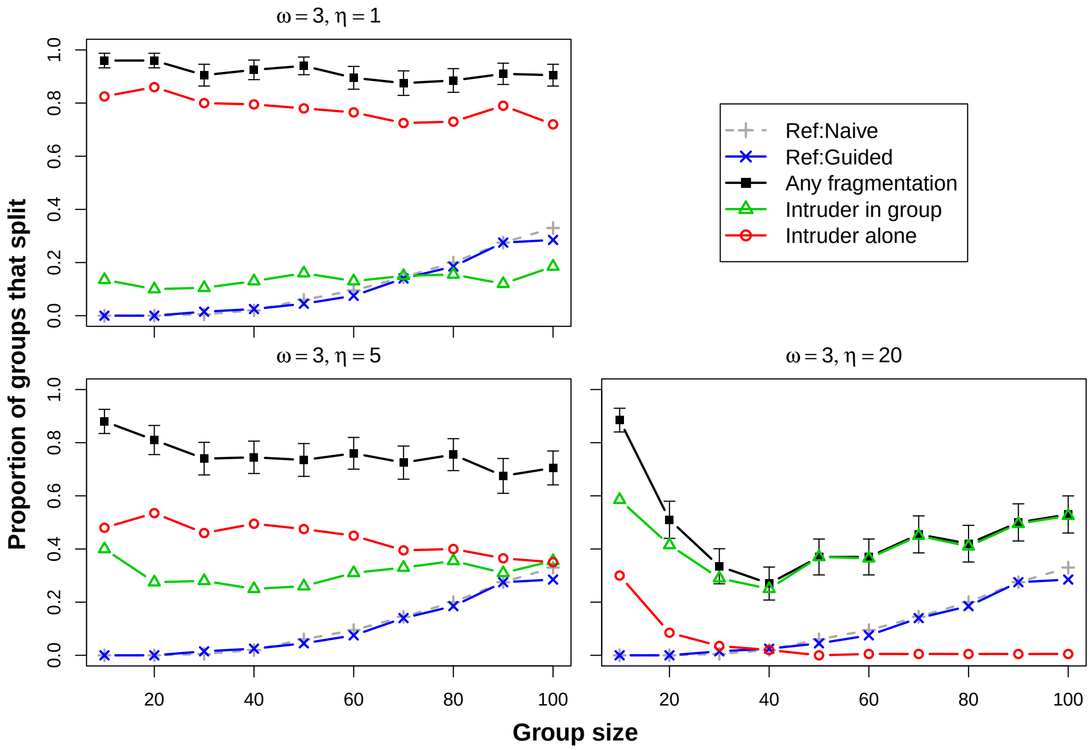


Figure 4.9: Changes in fragmentation based on credibility

Using credibility seems to have a positive effect on reaching targets and Figure 4.10 finally shows results we were hoping for. As credibility grows so does the group's interest in the secondary target. More precisely, it seems to sway those who were otherwise undecided or just not close enough before. The real treat comes with the highest degree of credibility $\eta = 20$. With increasing group size the shift in preferences becomes more and more apparent. Primary target is reached much less frequently. Although the secondary target does not achieve the same level of popularity as the primary one when the credibility is lower it is still a great accomplishment. Also, contrary to other cases it seems that most groups actually reach either target instead of being too far.

With the exception of its highest value, the usage of credibility even improves the chances to reach the primary target. This is mostly happening for medium assertiveness of $\omega = 0.5$, as we can see in Figure B.2, but it still applies for other values as well to a lesser extent. At first sight it might be a little surprising. However when we think about it a little more we can see the cause to be probably the intruder himself. There is no guarantee that majority of individuals will follow him when the group fragments or that they will even do so if he does not have high enough influence over them. Additionally, if he does not split away from the group he might involuntarily strenghten the drive of others to follow guides.

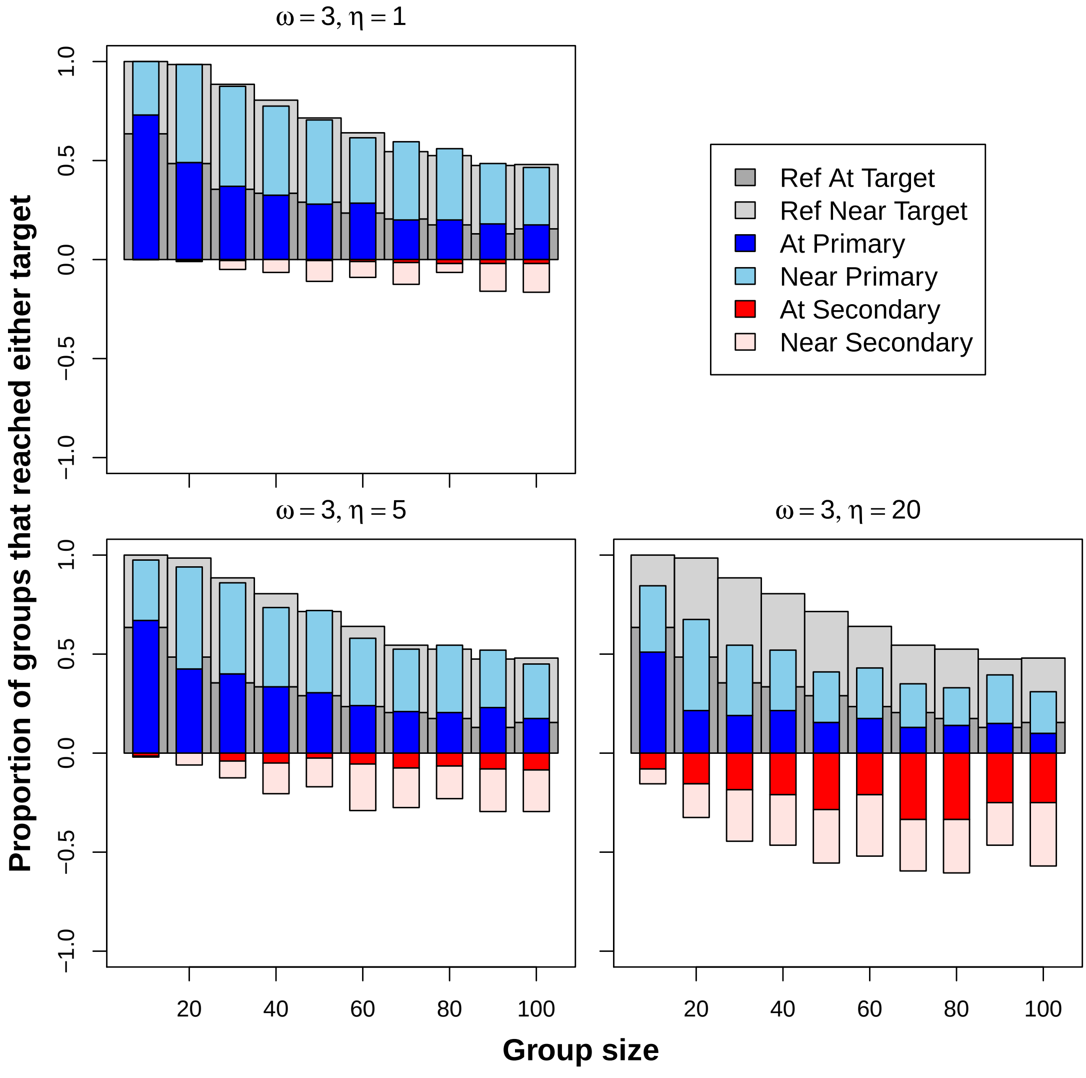


Figure 4.10: Changes in reaching targets based on credibility

Conclusion

At the beginning, we have made a few goals, or questions, for ourselves towards which we wanted to find some answers. With results at our disposal we are able to do so. Although we already briefly went through them, it was just a general observation. Here we present them directly in relation to said questions. Additionally, as we conclude our work we can see the outcomes of our many decisions. Not all of them turned out for the better, but that just allows us to reflect upon them. There are countless possibilities where to take this further using what we learned and our imagination. We mention a few of them later in this chapter.

Discussion

We have come across various results. Some of them were expected and some of them turned out as we hoped for. However we can also see that the parameters cover quite a great range with even larger gaps between values. We can say that we went for extreme values. That in itself certainly had an effect on how the results turned out. We had our reasons for it. The main one was that we wanted to explore this great range to find a case that would bring satisfying results. Of course, there are some disadvantages as well. For example, we lost the chance to identify specific thresholds when the behaviour changes or to do some fine-tuning of parameters to receive better results.

Now, how do the goals relate to this work? Why did we choose them? Contrary to most of other works that consider whole subgroups we focus on one individual alone, the intruder. The power of one should not be as effective as that of many but it is more interesting because of it. By taking control over the group he disrupts its original movement. Group's original cohesion is disrupted if his presence changes how it usually fragments. Thanks to previous works there are not many surprises under normal circumstances. That is why we added credibility and why we are interested in the changes it might cause.

Can one individual take control over already guided group?

Before answering we should explain the question so that there are no misunderstandings. For start, we consider only guided groups. Those are groups of any size consisting of an informed minority determining the group's destination and the rest of naive members. We do not expect just about anyone to be able to succeed. The individual must be informed about a target different from that of those guiding the group. Finally, to take control means to persuade the majority of the original group to follow the one interfering with guides.

Back to the question. The short answer is no, he cannot. At least in our circumstances which were similar to those in some of the other works [16]. They used mostly groups instead of individuals but given the results it only intensifies the futility of one's efforts. Therefore this answer does not really come as a surprise. Its main role was to confirm what was already known and to prepare the ground for other possibilities.

To elaborate on this further there are generally two possible outcomes. The defining factor is degree of assertiveness ω of the individual. Up to its certain threshold value he remains with the group behaving like the others. His intentions are not important enough for him to abandon the advantages of being in a group. When it goes past that threshold he leaves the group alone to pursue his own goals. The higher it is the earlier he will leave. Other individuals are not inclined to follow him and the cases when they do are rather rare.

When fragmentation occurs, is the intruder more prone to split alone or in a group?

We cannot always prevent groups from fragmenting even if there is no outside force causing it. There were no obstacles or any other such elements in our experiments that would deliberately try to divide the group. And yet groups still fragmented with increasing frequency as they grew in numbers. It did not matter if there are only naive individuals or some informed ones as well. All the individuals remained cohesive as one entity only when there were 10 or 20 of them.

Identifying cases when the intruder ends up alone is quite easy. We can see it even from visualizations. The other case becomes a little more complex. How do we separate cases when the intruder breaks away from the group and takes some of the individuals with himself from when the group just fragments? We took a simple approach. We ignore this difference and consider both of these the same. Therefore we basically consider only three options. The first is no fragmentation which does not happen that much. The second is intruder ending up alone. The third one is everything else except stray agents other than intruders.

So which one of the latter two happens more often? We touched upon this briefly in previous goal. It depends on intruder's degree of assertiveness ω. There is not much change at lower values while he stays with the group from when there is no intruder. But majority of fragmentation is due to the intruder leaving the group alone as we increase it beyond the threshold. The higher the degree of assertiveness is the higher the probablity of it happening. Furthermore, the other fragmentations are still present and even for small group sizes for which there were previously none. Also contrary to medium assertiveness their amount is not increasing with size but it remains similar across all of the sizes.

How does higher social status of the intruder affect possible outcomes?

In other words, does the inclusion of credibility in the model change anything? Does it have any effect? Yes it does, as we can say with satisfaction upon seeing the results. And in more ways than just one. At the beginning we were not really sure about what to expect. We hoped for satisfactory results and tried to set the parameters in a way we believed would make it more possible but there was still some uncertainty left. Fortunately we can now inspect these changes instead of repeating old news while declaring this a failure or a wrong way to go.

The intruder's efforts have little to no effect on the whole group when he is just another one of the masses. His chances to take control over it are almost non-existent. However this changes when he is considered as someone more important, when his credibility is higher than that of others. Little by little he starts by influencing those undecided and continues to persuade even the rest. The higher his credibility the more successful he is. It becomes even easier with increasing number of naive individuals and his own assertiveness. We can say that under suitable conditions one individual with high enough credibility is able to take control over a group. And in the worst case, his influence is at least significant enough to ensure some change.

Fragmentation is affected in a similar sense. For medium degree of assertiveness the inclusion of credibility does not make much difference. The group splits slightly more frequently as it increases but nothing more. Higher assertiveness shows more interesting behaviour. With gradually increasing credibility the intruder ends up much less alone and more in company of others. The probabilities of both of these slowly approach each other while completely swapping in the end. Moreover, the intruder stops ending up alone when there is a sufficient number of naive individuals and his credibility is high enough. This is most likely a consequence of his high influence. The others follow him even if he does not care about them and follows his own goals.

As we can see the addition of credibility does exactly what it was intended to do. It gives the individual an influence. It makes him more visible to others and his voice is heard more clearly. He becomes important. Where he was previously unable to even change the course of group's movement he is now the center of attention. Where he was previously splitting away alone he is now followed by the majority. It certainly adds another layer to the whole set of interactions between individuals. But it is not as simple as it seems. Credibility would not be as effective by itself if it was not for other parameters. The most apparent of them seem to be group size and individual's degree of assertiveness. There might more but it was not our goal to identify them.

The bigger the group the greater the effect. Even if it might be different for much larger sizes of thousands and more we still see it happening on numerous occasions for sizes we covered. The naivety of most group members is most likely closely related to it. At least as far as our model and its implementation are concerned. Group size might not be as relevant as it is if most of the group's members were informed. So in our case naivety in numbers makes it easier for one individual to influence them. That in itself is an interesting observation because Couzin et al.'s previous work [16] suggests the opposite. They note how it promotes democracy and inhibits opinionated minority. However with high enough credibility applied the minority becomes a majority in the eyes of uninformed masses.

When the individual intends to influence others it is better for him if they are naive and in sufficient numbers. However, he also needs to know what to do. He needs a determination to follow his goal. Otherwise he might only support someone else. In this sense, credibility by itself is sort of like a double-edged sword. And one's degree of assertiveness determines how sharp its edges are. It tells which edge is to be used. How do they relate to each other? When the individual has high credibility but low assertiveness he simply follows those around him and strenghtens their decisions. On the other hand, low credibility and high assertiveness only makes him leave the group. Simply put, the individual needs to be intent on following his own goals first and foremost to be able to persuade others to accept his opinions. If he is not he just becomes a puppet promoting the goals of others.

Overall Impressions

We have shown that while a normal individual cannot do much to disrupt the whole group, he becomes able to do so when he is acknowledged by others. Just one influential member of a group can determine its behaviour when the conditions are in his favour. In other words, a normal random error occuring in a system might not be of much significance. However there is still some possibility that it might lead to unforseen consequences if the error turns out to be not as normal as we thought. There is still a lot of things to improve upon or to do better but we believe that we have accomplished our goals and the purpose of this work. We have shown that credibility plays a major part in the resulting behaviour if it is accounted for.

Although we are satisfied in general, we still have one concern. That is the possibility of the intruder becoming an actual leader. The majority of the most satisfactory results were observed for outlying values. Credibility far higher than the normal one. Assertiveness highly promoting one's own goals and almost ignoring the group. Is it reasonable to use these values? Are not we just somehow creating a leader? It might seem that we contradict ourselves with this. We wanted to make him influential enough to take control. We wanted him to overrule others. But we still want the group to behave like a swarm, a decentralized system of locally interacting individuals. The intruder does not directly command those around him but his word might have such a significance to them that it might get very close to it. For this reason we find it questionable but at the same time we are unable to form a definite answer.

Future Work

There still exist several ways to improve the work presented in this thesis, as well as several possibilities to reconsider the approach or point of view. These can serve as an inspiration for future research which we outline briefly in this section. The most integral part are the simulation tools we developed and used. Since we made them to allow for more general usage we lost the opportunity to get better and more precise results. This limited us in what we could work with. Directly related to this is data representation which we tried to make simple and comprehensible at the same time. Another thing that we touched only briefly is statistical processing of data. There could certainly be done more stuff than just the basic summary we did. Mainly dependency of various parameters would be really good to have.

Nevertheless, it can still be used as a starting point for further research. One way to do so is to expand upon the current setting. The experiments would certainly benefit from being done in dedicated tools with better output. It would really help if we could observe the behaviour in greater detail; like being able to work with data from the middle of the experiment and not only the end. The results would be more accurate. The overall scope of experiments could be increased. We explored just the most important parameters and a few of their values with large gaps between them. These gaps could be filled and other values added. Parameters that had static values could be explored as well. There is a lot of room to find dependencies, thresholds and to do some fine-tuning. We have shown what is possible under specific conditions but those are not the only ones.

Another way for further research is straightforward. We have introduced credibility into the model and then we have shown that its presence does make a difference. But we have only scraped the surface of it and there is more than one way to take it after this. For one thing, it could be implemented differently. We used a certain approach which was based mainly on mathematics. It might be interesting to push it towards more natural foundations. We have used it on only one individual but it can be applied to others as well. It could create sort of a hierarchy or a caste system in a group. Also similarly to other parameters we tried only a few values and the observed changes were rather abrupt. It would be good to find specific thresholds. Surely, there are even more possibilities to explore and things to try with it. We hope that others will find it interesting and research it further.

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Attachments

A. Environment

To conduct all of the experiments we first needed to implement the model. But not just any environment would be sufficient enough for us. There was an option to use one of the many toolsets that are readily available and we even considered it. However, we had a few requirements we were expecting it to meet and other limitations we had to follow. That together with our desire to improve on our own coding skills ultimately made us decide to create our own toolset from the ground up.

A.1 Specification

The toolset is implemented in `C#` under .NET 4.0 framework. Graphical user interface is written in WPF. Microsoft Visual Studio 2010 is used as development environment. It is being developed for Windows operating system and there is no cross-platform compatibility planned. Third party libraries are used for visualizing and randomization. Other might be added if the need arises. The name of the toolset is *Muragatte*.

The key features are as follows:

- **Customization** The toolset should provide enough options to run a variety of different experiments even beyond the scope of this thesis and its model.
- **Repeatability** We should be able to repeat any experiment using the same starting settings and get the same results.
- **Save/Load** We should be able to save the completed experiment along with its settings and anything else needed so that we can load it later to rerun or review it.
- **Visualization** The toolset should provide visualizations of simulations and it should allow for at least partial customization of the overall look.

Apart from various third party libraries the toolset is expected to consist of five parts:

- **The Core** Library. The foundation for everything else. The model and its variations. Controls the simulation itself.
- **The Visual** Library. Visualization capabilities and its customization.
- **The Tool** Application. Main interface to work with experiments. Extensive settings available. More generalized.

- **The Batch** Application. Simplified interface to run a set of experiments with similar setting.
- **The Sandbox** Application. Interactive realtime simulations. Mainly for testing. Not that important.

A.2 Implementation

From the start we intended for the toolset to be more general in scope. Although it was not the best decision in regards to the thesis we believed we could get a piece of software that could be used for a variety of tasks and not just the one we needed. It was basically an investment to the future that might not even come. Since we deal with swarming behaviour we took an agent-based model approach towards the implementation. Among other things, it allowed us to keep the model logic and the system logic separated.

We ended up using a few third party libraries in various parts of the toolset. *DotNetZip* [20] made it easier for us to work with ZIP files which were utilised in some of the output. *Extended WPF Toolkit* [23] provided us with many useful WPF controls to make better graphical user interface. *RandomOps* [57] was used for its implementation of mt19937 variant of Mersenne Twister algorithm [48] as the pseudo-random number generator. *WriteableBitmapEx* [70] was included to handle drawing of visualizations.

A.2.1 The Core (*MuragatteCore*)

It handles the inner workings together with other foundations to have a functional simulation. The simulation is run in discrete steps at which all elements are updated to new state according to their rules. The elements cover both agents and other objects like obstacles, targets, centroids, etc. Agents are representations of specific model implementations. There is a variety of steering rules available to build upon as well as a few agents of different behaviour. Every element operates inside a region of defined size and continuity. The system can keep a history of all previous states of elements which can then be used for visualization or the computation of results.

The performance of the system is largely influenced by the data structure the elements are stored in since there is a lot of interaction going on. At the latest version there is only a simple list structure available which results in the complexity of $O(n^2)$. We originally considered using Orthant Neighbourhood Graphs proposed by Germer and Strothotte [26] but we ultmately decided against it. There were a few reasons for it. First was the lack of other reference materials.

Second was the effort and time needed to integrate it into our system both of which would be better used elsewhere. Finally there was a questionable gain in performance for the relatively small scope of our intended experiments. We simply weren't sure that the advantages in proximity search would overweight the constant need for structure maintenance. Although unused, the remnants of its incomplete implementation are still left in the source code. We did not consider other options since we thought the simple list structure would suffice.

A.2.2 The Visual (*MuragatteVisual*)

It provides the interface for visualization of simulation. Its capabilities were mainly inspired by SwarmVis [50]. The customization options include scale of the scene, colors of both background and various elements and effects, and shape of elements among other things. The scene is drawn in layers depending on what is enabled in the order of environmental objects (like targets or obstacles), neighbourhoods (only field of view), tracks (complete path from start), trails (a few previous positions), agents, and centroids (an average of each group). Every element can also be highlighted. Furthermore, the selection of elements and effects to draw can be done both individually and by a selection filter of species/type or group. It also allows to save customized snapshots in PNG file format.

A.2.3 The Tool (*MuragatteResearch*)

It is the most integral part of the toolset for communication with user. Its base working unit is an experiment which is a simulation from The Core encompassed in a pack with other customization options. Apart from the simulation related options the most important ones for experiment are length, number of runs, and seed for pseudo-random number generator. The seed is used to ensure repeatability of experiments because randomization is used both at initialization and for noise at each simulation step. Only one experiment is active and worked on at a time. The available operations include creation, saving, loading, editing, running, reviewing of results and visualizing.

Creation and modification of experiments is done through editor windows each of which is dedicated to different task. The top one is for experiment itself. It contains the main options and also serves as a starting point to go to others. Styles editor determines the visual look of elements. Scene editor is for the environmental area and its objects. Species which provide further granularity to element types have their own editor as well. Lastly there is an archetype editor. An archetype is a definition for a group of agents of the same origin. We basically define one agent and how many of his copies should be made. Although only predefined archetypes/agents can be used they should allow for more than enough customization.

It allows a great freedom in what experiments can be made but on the other hand the results are quite lacking. They are a basic summary containing information about experiment as a whole, each of its runs, and each of its steps. At all of those levels it says how many groups and stray agents there were, a litttle summary about main group, and that of selected archetypes. It gives some information but it is not very useful for specific scenarios.

The output consists of a few things. Settings of both the whole experiment and its parts can be saved into XML files. For completed experiments, part of the results can be saved in a couple of TXT files and the whole history can be saved into one ZIP file per run, or instance as it is called internally. Each of these ZIP files then contains a TXT file for every step with status of all elements at that point.

For more details see user manual [64].

A.2.4 The Batch (*MuragatteThesis*)

It was abandoned and almost comletely dropped out of the toolset in the early stage of development. At the time it felt better to merge its functionality into The Tool. However it was reintroduced with some changes in the final stages because The Tool became too general. Mainly its handling of results was insufficient and almost unsuitable in regards to the thesis. Therefore it was reimagined as more focused and specialized on experiments and our needs. It provided three main features. First were the results. We mostly did them from scratch getting only what was really important and using the ones from The Tool as an occasional reference. We also added layered visualizations. The second was heavily simplified initialization to just a few options. The third was running the experiments in batches based on group size. It was used to conduct the experiments.

A.2.5 The Sandbox (*MuragatteSandbox*)

It was mainly used in the beginning phases of development as a stand-in and a testing interface. This treatment continued up until there was a functional prototype. After that any work on it was discontinued and it was effectively abandoned. Although it would be a welcome addition to the toolset as a whole it was not really required as far as the thesis was concerned. There was actually no work done towards its intended features. Apart from occasional updates to related stuff it remained in the state it was left in. Usage is not recommended.

A.3 Performance

For the purposes of this thesis we use revision 72 of the toolset which is also its latest version at the time of writing this. Although it is not the final version and it is thus incomplete, all the major features are implemented. It has not been tested for all the possibilities and the issues related to it but it is functional enough to fulfil our needs. We have not encountered any serious problems while using it to run the experiments. The only issue we encountered was most likely related to hardware limitations as it did not occur again under less demanding setting or on more powerful hardware. For details on known issues see user manual [64].

Please note that the simulation can be quite demanding in regards to both processing time and memory space. The bigger the scope, or more specifically the number of agents, the more noticeable it is. A slowdown can also occur while playing visualizations with additional effects enabled. Certain customization setting, like scale or color transparency, can slow it down as well. The overall experience may vary depending on used hardware.

A.4 Output

MuragatteThesis saves results to a text file with default extension $*$.DAT. The first line of the file contains headers. Each line after that stands for one entry – one run of an experiment. Each column stands for one attribute. Table A.1 explains the meanings and possible values for all columns. The last line is usually incomplete when an experiment is cancelled. For details on other output options see user manual [64].

Label	–	Description
	–	**Possible Values** [**Experiment Values**]
Run	–	Sequential number of experiment's run.
	–	$x \geq 0$ with maximum based on initialization [$0 \leq x \leq 199$]
N	–	Total number of agents.
	–	based on initialization where $x \geq 6$ [10, 20, 30, ..., 100]
N.n	–	Number of Naive agents.
	–	$N - N.g - N.i$
N.g	–	Number of Guides.
	–	0 or 5
N.i	–	Number of Intruders.
	–	0 or 1 [always 0 if $N.g = 0$]
Assert	–	Intruder's degree of assertiveness.
	–	0 (only if $N.i = 0$), 0.5, 1, 3
Cred	–	Intruder's degree of credibility.
	–	0 (only if $N.i = 0$), 1, 2, 5, 20
Groups	–	Number of groups at the end of simulation.
	–	$1 \leq x \leq \lfloor N/2 \rfloor$
Strays	–	Number of stray agents at the end of simulation.
	–	$0 \leq x \leq N$
Size	–	Main group's size at the end of simulation.
	–	$\lceil N/2 \rceil \leq x \leq N$
Size.g	–	Size of a group containing the majority of Guides at the end of simulation.
	–	0 if $N.g = 0$ $3 \leq x \leq N$ otherwise
Size.i	–	Size of a group containing the Intruder at the end of simulation.
	–	0 if $N.i = 0$ $1 \leq x \leq N$ otherwise
Dist.g	–	Minimum distance between main group and Guides' target. Absolute distance between centers of target and the nearest agent.
	–	≥ 0.000
Dist.i	–	Minimum distance between main group and Intruder's target. Absolute distance between centers of target and the nearest agent.
	–	≥ 0.000
IDist	–	Distance between the Intruder and his target at the end of simulation. Absolute distance between centers.
	–	0.000 if $N.i = 0$ ≥ 0.000 otherwise

Table A.1: File format description for results output of MuragatteThesis application. *Experiment Values* further specify the result values of our experiments. All attributes have an integer value with the exception of *Assert*, *Dist.g*, *Dist.i*, and *IDist*. Distance values might contain ',' instead of '.' as a floating point symbol.

B. Additional Result Details

The following tables list mean values of relevant criteria in the range of 0–1. It represents a percentage of 0–100% of groups that satisfy required conditions. Their standard deviations and 95% confidence intervals are listed as well. An exception to this are Tables B.7, B.10 and B.11 and part of Table B.2 that show minimum, median and maximum values of absolute distances between agents and target in question.

B.1 Naive & Guided

	Naive			***Guided***		
Size	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
10	0	0	0	0	0	0
20	0	0	0	0	0	0
30	0.005	0.071	0.01	0.015	0.122	0.017
40	0.02	0.14	0.02	0.025	0.157	0.022
50	0.06	0.238	0.033	0.045	0.208	0.029
60	0.095	0.294	0.041	0.075	0.264	0.037
70	0.145	0.353	0.049	0.14	0.348	0.049
80	0.2	0.401	0.056	0.185	0.389	0.054
90	0.275	0.448	0.062	0.275	0.448	0.062
100	0.33	0.471	0.066	0.285	0.453	0.063

Table B.1: Fragmentation statistics: reference

	At			***Near***			***Distance***		
Size	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Min**	**Median**	**Max**
10	0.635	0.483	0.067	0.365	0.483	0.067	0.101	6.543	37.325
20	0.485	0.501	0.07	0.5	0.501	0.07	0.237	9.790	95.744
30	0.355	0.48	0.067	0.53	0.5	0.07	0.353	12.805	129.639
40	0.335	0.473	0.066	0.47	0.5	0.07	0.208	16.889	141.645
50	0.29	0.455	0.063	0.425	0.496	0.069	0.147	25.876	175.979
60	0.235	0.425	0.059	0.405	0.492	0.069	0.469	29.997	164.433
70	0.205	0.405	0.056	0.34	0.475	0.066	0.127	43.343	162.419
80	0.175	0.381	0.053	0.35	0.478	0.067	0.429	47.413	185.580
90	0.13	0.337	0.047	0.345	0.477	0.066	0.321	54.456	171.781
100	0.155	0.363	0.051	0.325	0.47	0.065	0.314	53.663	164.061

Table B.2: Target distance statistics: guided

B.2 Fragmentation

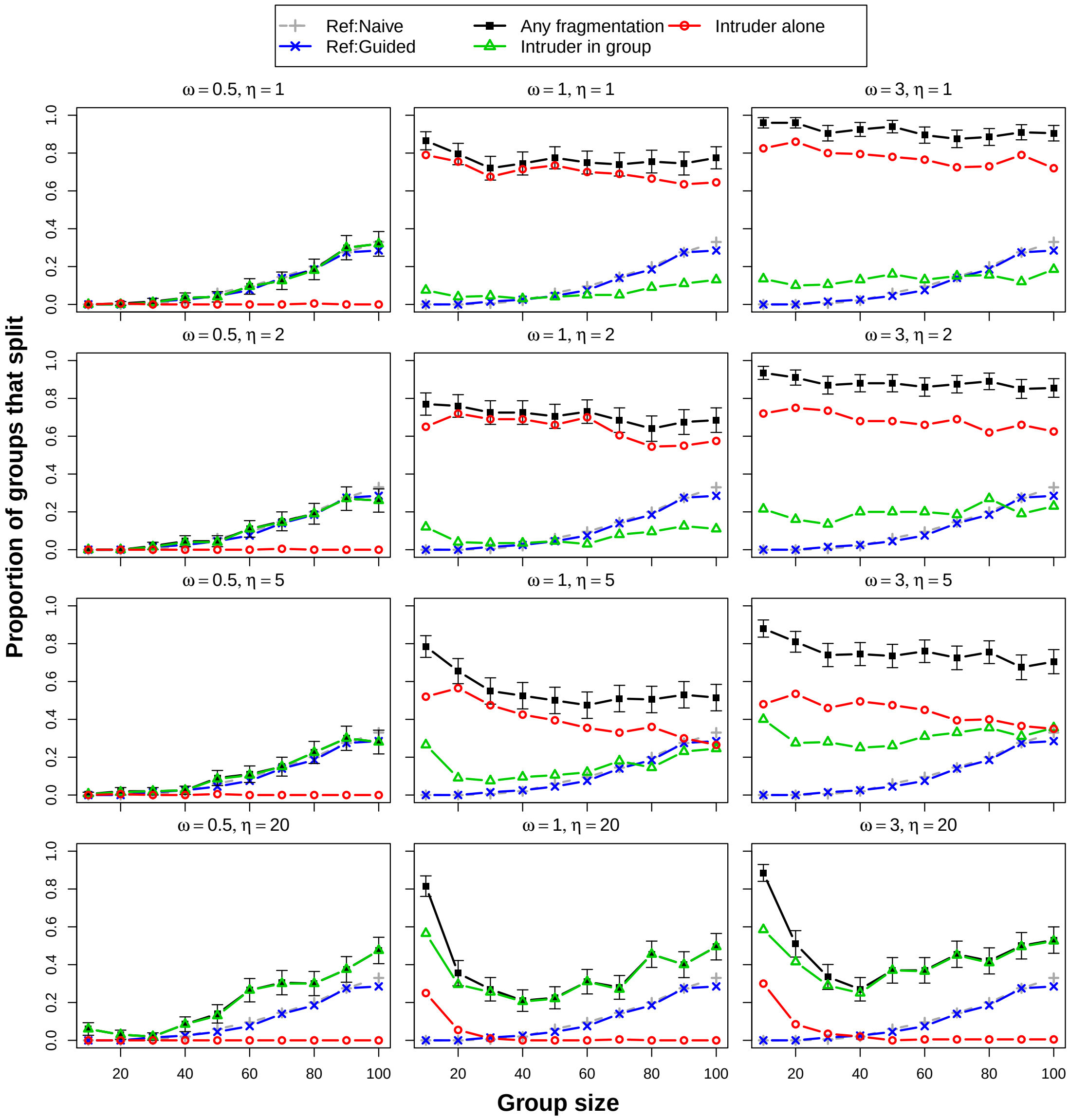

Figure B.1: Fragmentation comparison

	Size	$\omega = 0.5$ Mean	$\omega = 0.5$ ±SD	$\omega = 0.5$ ±CI	$\omega = 1$ Mean	$\omega = 1$ ±SD	$\omega = 1$ ±CI	$\omega = 3$ Mean	$\omega = 3$ ±SD	$\omega = 3$ ±CI
$\eta = 1$	10	0	0	0	0.075	0.264	0.037	0.135	0.343	0.048
	20	0	0	0	0.04	0.196	0.027	0.1	0.301	0.042
	30	0.01	0.1	0.014	0.045	0.208	0.029	0.105	0.307	0.043
	40	0.035	0.184	0.026	0.03	0.171	0.024	0.13	0.337	0.047
	50	0.04	0.196	0.027	0.04	0.196	0.027	0.16	0.368	0.051
	60	0.095	0.294	0.041	0.05	0.218	0.03	0.13	0.337	0.047
	70	0.125	0.332	0.046	0.05	0.218	0.03	0.15	0.358	0.05
	80	0.18	0.385	0.054	0.09	0.287	0.04	0.155	0.363	0.051
	90	0.3	0.459	0.064	0.11	0.314	0.044	0.12	0.326	0.045
	100	0.32	0.468	0.065	0.13	0.337	0.047	0.185	0.389	0.054
$\eta = 2$	10	0	0	0	0.12	0.326	0.045	0.215	0.412	0.057
	20	0	0	0	0.04	0.196	0.027	0.16	0.368	0.051
	30	0.015	0.122	0.017	0.035	0.184	0.026	0.135	0.343	0.048
	40	0.04	0.196	0.027	0.035	0.184	0.026	0.2	0.401	0.056
	50	0.04	0.196	0.027	0.045	0.208	0.029	0.2	0.401	0.056
	60	0.11	0.314	0.044	0.03	0.171	0.024	0.2	0.401	0.056
	70	0.145	0.353	0.049	0.08	0.272	0.038	0.185	0.389	0.054
	80	0.19	0.393	0.055	0.095	0.294	0.041	0.27	0.445	0.062
	90	0.27	0.445	0.062	0.125	0.332	0.046	0.190	0.393	0.055
	100	0.26	0.44	0.061	0.11	0.314	0.044	0.23	0.422	0.059
$\eta = 5$	10	0.005	0.071	0.01	0.265	0.442	0.062	0.4	0.491	0.068
	20	0.015	0.122	0.017	0.09	0.287	0.04	0.275	0.448	0.062
	30	0.02	0.14	0.02	0.075	0.264	0.037	0.28	0.45	0.063
	40	0.025	0.157	0.022	0.095	0.294	0.041	0.25	0.434	0.061
	50	0.085	0.28	0.039	0.105	0.307	0.043	0.26	0.44	0.061
	60	0.105	0.307	0.043	0.12	0.326	0.045	0.31	0.464	0.065
	70	0.15	0.358	0.05	0.18	0.385	0.054	0.33	0.471	0.066
	80	0.225	0.419	0.058	0.145	0.353	0.049	0.355	0.48	0.067
	90	0.3	0.459	0.064	0.23	0.422	0.059	0.31	0.464	0.065
	100	0.28	0.45	0.063	0.245	0.431	0.06	0.355	0.48	0.067
$\eta = 20$	10	0.06	0.238	0.033	0.565	0.497	0.069	0.585	0.494	0.069
	20	0.03	0.171	0.024	0.295	0.457	0.064	0.415	0.494	0.069
	30	0.02	0.14	0.02	0.255	0.437	0.061	0.29	0.455	0.063
	40	0.085	0.28	0.039	0.205	0.405	0.056	0.25	0.434	0.061
	50	0.13	0.337	0.047	0.22	0.415	0.058	0.37	0.484	0.067
	60	0.265	0.442	0.062	0.31	0.464	0.065	0.365	0.483	0.067
	70	0.3	0.459	0.064	0.27	0.445	0.062	0.45	0.499	0.07
	80	0.3	0.459	0.064	0.455	0.499	0.07	0.41	0.493	0.069
	90	0.375	0.485	0.068	0.4	0.491	0.068	0.495	0.501	0.07
	100	0.475	0.501	0.07	0.495	0.501	0.07	0.525	0.501	0.07

Table B.3: Fragmentation statistics: intruder in group

	Size	$\omega = 0.5$ Mean	±SD	±CI	$\omega = 1$ Mean	±SD	±CI	$\omega = 3$ Mean	±SD	±CI
$\eta = 1$	10	0	0	0	0.79	0.408	0.057	0.825	0.381	0.053
	20	0.005	0.071	0.01	0.755	0.431	0.06	0.86	0.348	0.049
	30	0	0	0	0.675	0.47	0.065	0.8	0.401	0.056
	40	0	0	0	0.715	0.453	0.063	0.795	0.405	0.056
	50	0	0	0	0.735	0.442	0.062	0.78	0.415	0.058
	60	0	0	0	0.7	0.459	0.064	0.765	0.425	0.059
	70	0	0	0	0.69	0.464	0.065	0.725	0.448	0.062
	80	0.005	0.071	0.01	0.665	0.473	0.066	0.73	0.445	0.062
	90	0	0	0	0.635	0.483	0.067	0.79	0.408	0.057
	100	0	0	0	0.645	0.48	0.067	0.72	0.45	0.063
$\eta = 2$	10	0	0	0	0.65	0.478	0.067	0.72	0.45	0.063
	20	0	0	0	0.72	0.45	0.063	0.75	0.434	0.061
	30	0	0	0	0.69	0.464	0.065	0.735	0.442	0.062
	40	0	0	0	0.69	0.464	0.065	0.68	0.468	0.065
	50	0	0	0	0.66	0.475	0.066	0.68	0.468	0.065
	60	0	0	0	0.7	0.459	0.064	0.66	0.475	0.066
	70	0.005	0.071	0.010	0.605	0.49	0.068	0.69	0.464	0.065
	80	0	0	0	0.545	0.499	0.07	0.62	0.487	0.068
	90	0	0	0	0.55	0.499	0.07	0.66	0.475	0.066
	100	0	0	0	0.575	0.496	0.069	0.625	0.485	0.068
$\eta = 5$	10	0	0	0	0.52	0.501	0.07	0.48	0.501	0.07
	20	0.005	0.071	0.010	0.565	0.497	0.069	0.535	0.5	0.07
	30	0	0	0	0.475	0.501	0.07	0.46	0.5	0.07
	40	0	0	0	0.425	0.496	0.069	0.495	0.501	0.07
	50	0.005	0.071	0.010	0.395	0.49	0.068	0.475	0.501	0.07
	60	0	0	0	0.355	0.48	0.067	0.45	0.499	0.07
	70	0	0	0	0.33	0.471	0.066	0.395	0.49	0.068
	80	0	0	0	0.36	0.481	0.067	0.4	0.491	0.068
	90	0	0	0	0.3	0.459	0.064	0.365	0.483	0.067
	100	0	0	0	0.265	0.442	0.062	0.35	0.478	0.067
$\eta = 20$	10	0	0	0	0.25	0.434	0.061	0.3	0.459	0.064
	20	0	0	0	0.055	0.229	0.032	0.085	0.28	0.039
	30	0	0	0	0.01	0.1	0.014	0.035	0.184	0.026
	40	0	0	0	0	0	0	0.02	0.14	0.02
	50	0	0	0	0	0	0	0	0	0
	60	0	0	0	0	0	0	0.005	0.071	0.01
	70	0	0	0	0.005	0.071	0.01	0.005	0.071	0.01
	80	0	0	0	0	0	0	0.005	0.071	0.01
	90	0	0	0	0	0	0	0.005	0.071	0.01
	100	0	0	0	0	0	0	0.005	0.071	0.01

Table B.4: Fragmentation statistics: intruder alone

B.3 Target Distance

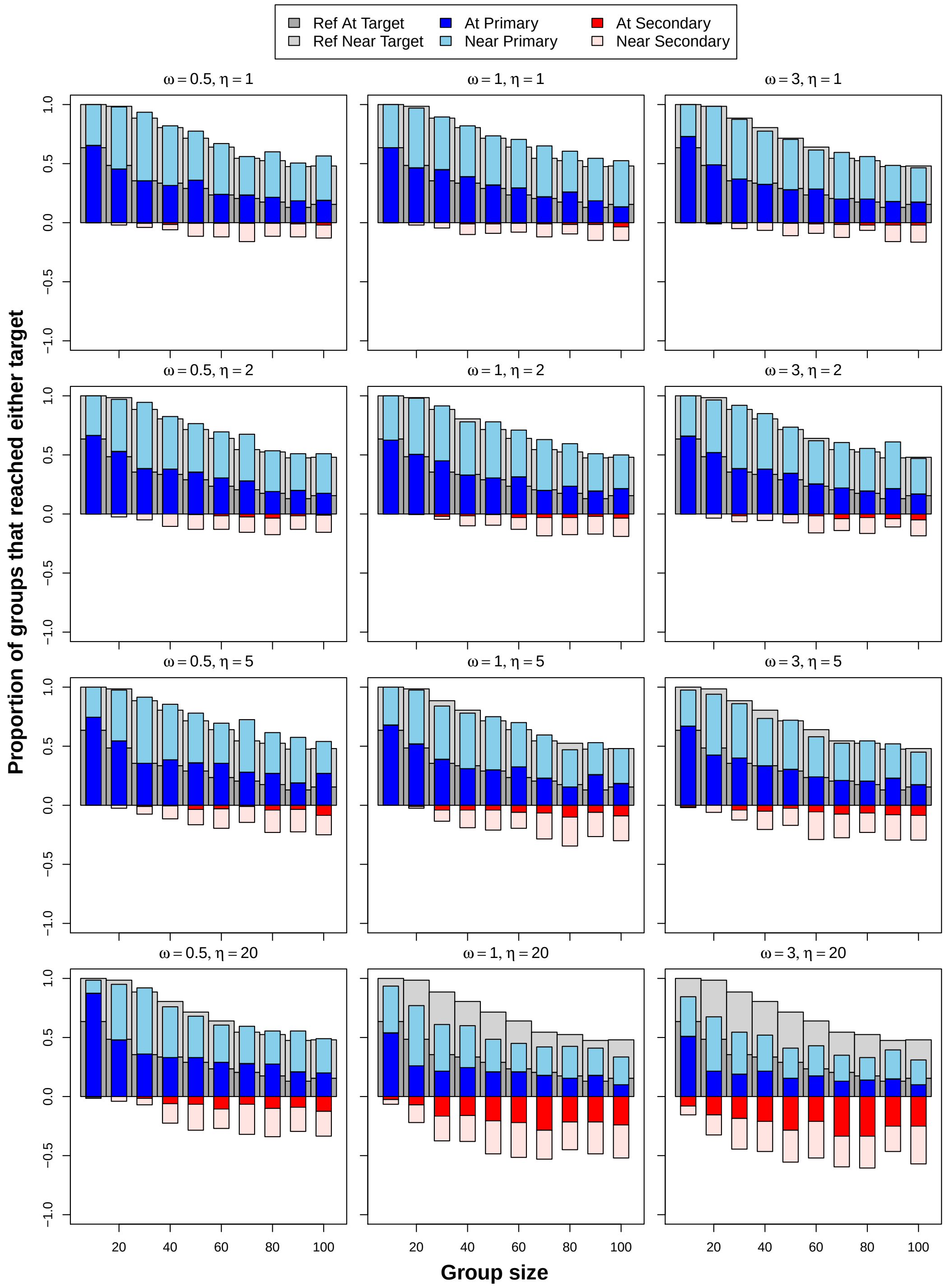

Figure B.2: Target distance comparison

	Size	ω = 0.5 Mean	±SD	±CI	ω = 1 Mean	±SD	±CI	ω = 3 Mean	±SD	±CI
$\eta = 1$	10	0.655	0.477	0.066	0.635	0.483	0.067	0.73	0.445	0.062
	20	0.455	0.499	0.07	0.465	0.5	0.07	0.49	0.501	0.07
	30	0.355	0.48	0.067	0.45	0.499	0.07	0.37	0.484	0.067
	40	0.315	0.466	0.065	0.39	0.489	0.068	0.325	0.47	0.065
	50	0.36	0.481	0.067	0.32	0.468	0.065	0.28	0.45	0.063
	60	0.24	0.428	0.06	0.295	0.457	0.064	0.285	0.453	0.063
	70	0.235	0.425	0.059	0.22	0.415	0.058	0.2	0.401	0.056
	80	0.215	0.412	0.057	0.26	0.44	0.061	0.2	0.401	0.056
	90	0.185	0.389	0.054	0.185	0.389	0.054	0.18	0.385	0.054
	100	0.19	0.393	0.055	0.135	0.343	0.048	0.175	0.381	0.053
$\eta = 2$	10	0.665	0.473	0.066	0.625	0.485	0.068	0.66	0.475	0.066
	20	0.53	0.5	0.07	0.505	0.501	0.07	0.52	0.501	0.07
	30	0.385	0.488	0.068	0.45	0.499	0.07	0.385	0.488	0.068
	40	0.38	0.487	0.068	0.33	0.471	0.066	0.38	0.487	0.068
	50	0.355	0.48	0.067	0.305	0.462	0.064	0.345	0.477	0.066
	60	0.305	0.462	0.064	0.315	0.466	0.065	0.255	0.437	0.061
	70	0.28	0.45	0.063	0.2	0.401	0.056	0.22	0.415	0.058
	80	0.19	0.393	0.055	0.235	0.425	0.059	0.195	0.397	0.055
	90	0.2	0.401	0.056	0.195	0.397	0.055	0.215	0.412	0.057
	100	0.175	0.381	0.053	0.215	0.412	0.057	0.17	0.377	0.053
$\eta = 5$	10	0.745	0.437	0.061	0.68	0.468	0.065	0.67	0.471	0.066
	20	0.545	0.499	0.07	0.52	0.501	0.07	0.425	0.496	0.069
	30	0.355	0.48	0.067	0.39	0.489	0.068	0.4	0.491	0.068
	40	0.385	0.488	0.068	0.31	0.464	0.065	0.335	0.473	0.066
	50	0.36	0.481	0.067	0.3	0.459	0.064	0.305	0.462	0.064
	60	0.355	0.48	0.067	0.325	0.47	0.065	0.24	0.428	0.06
	70	0.28	0.45	0.063	0.23	0.422	0.059	0.21	0.408	0.057
	80	0.27	0.445	0.062	0.155	0.363	0.051	0.205	0.405	0.056
	90	0.19	0.393	0.055	0.26	0.440	0.061	0.23	0.422	0.059
	100	0.27	0.445	0.062	0.185	0.389	0.054	0.175	0.381	0.053
$\eta = 20$	10	0.875	0.332	0.046	0.54	0.5	0.07	0.51	0.501	0.07
	20	0.48	0.501	0.07	0.26	0.44	0.061	0.215	0.412	0.057
	30	0.36	0.481	0.067	0.215	0.412	0.057	0.19	0.393	0.055
	40	0.33	0.471	0.066	0.245	0.431	0.06	0.215	0.412	0.057
	50	0.33	0.471	0.066	0.21	0.408	0.057	0.155	0.363	0.051
	60	0.29	0.455	0.063	0.21	0.408	0.057	0.175	0.381	0.053
	70	0.28	0.45	0.063	0.18	0.385	0.054	0.13	0.337	0.047
	80	0.275	0.448	0.062	0.155	0.363	0.051	0.14	0.348	0.049
	90	0.21	0.408	0.057	0.18	0.385	0.054	0.15	0.358	0.05
	100	0.2	0.401	0.056	0.1	0.301	0.042	0.1	0.301	0.042

Table B.5: Target distance statistics: at primary target

	Size	ω = 0.5 Mean	±SD	±CI	ω = 1 Mean	±SD	±CI	ω = 3 Mean	±SD	±CI
$\eta = 1$	10	0.345	0.477	0.066	0.365	0.483	0.067	0.27	0.445	0.062
	20	0.525	0.501	0.07	0.505	0.501	0.07	0.495	0.501	0.07
	30	0.58	0.495	0.069	0.445	0.498	0.069	0.505	0.501	0.07
	40	0.505	0.501	0.07	0.43	0.496	0.069	0.45	0.499	0.07
	50	0.415	0.494	0.069	0.415	0.494	0.069	0.425	0.496	0.069
	60	0.43	0.496	0.069	0.41	0.493	0.069	0.33	0.471	0.066
	70	0.325	0.47	0.065	0.43	0.496	0.069	0.395	0.49	0.068
	80	0.385	0.488	0.068	0.345	0.477	0.066	0.36	0.481	0.067
	90	0.32	0.468	0.065	0.36	0.481	0.067	0.305	0.462	0.064
	100	0.375	0.485	0.068	0.39	0.489	0.068	0.29	0.455	0.063
$\eta = 2$	10	0.335	0.473	0.066	0.375	0.485	0.068	0.34	0.475	0.066
	20	0.44	0.498	0.069	0.475	0.501	0.07	0.445	0.498	0.069
	30	0.56	0.498	0.069	0.465	0.5	0.07	0.535	0.5	0.07
	40	0.445	0.498	0.069	0.45	0.499	0.07	0.47	0.5	0.07
	50	0.41	0.493	0.069	0.475	0.501	0.07	0.39	0.489	0.068
	60	0.39	0.489	0.068	0.395	0.49	0.068	0.365	0.483	0.067
	70	0.395	0.49	0.068	0.43	0.496	0.069	0.385	0.488	0.068
	80	0.345	0.477	0.066	0.36	0.481	0.067	0.36	0.481	0.067
	90	0.31	0.464	0.065	0.315	0.466	0.065	0.395	0.49	0.068
	100	0.335	0.473	0.066	0.285	0.453	0.063	0.3	0.459	0.064
$\eta = 5$	10	0.255	0.437	0.061	0.32	0.468	0.065	0.305	0.462	0.064
	20	0.43	0.496	0.069	0.455	0.499	0.07	0.515	0.501	0.07
	30	0.56	0.498	0.069	0.45	0.499	0.07	0.46	0.5	0.07
	40	0.47	0.5	0.07	0.47	0.5	0.07	0.4	0.491	0.068
	50	0.42	0.495	0.069	0.45	0.499	0.07	0.415	0.494	0.069
	60	0.34	0.475	0.066	0.375	0.485	0.068	0.34	0.475	0.066
	70	0.445	0.498	0.069	0.365	0.483	0.067	0.315	0.466	0.065
	80	0.345	0.477	0.066	0.315	0.466	0.065	0.34	0.475	0.066
	90	0.385	0.488	0.068	0.27	0.445	0.062	0.29	0.455	0.063
	100	0.27	0.445	0.062	0.295	0.457	0.064	0.275	0.448	0.062
$\eta = 20$	10	0.11	0.314	0.044	0.395	0.49	0.068	0.335	0.473	0.066
	20	0.47	0.5	0.07	0.51	0.501	0.07	0.46	0.5	0.07
	30	0.56	0.498	0.069	0.395	0.49	0.068	0.355	0.48	0.067
	40	0.43	0.496	0.069	0.355	0.48	0.067	0.305	0.462	0.064
	50	0.35	0.478	0.067	0.275	0.448	0.062	0.255	0.437	0.061
	60	0.315	0.466	0.065	0.24	0.428	0.06	0.255	0.437	0.061
	70	0.315	0.466	0.065	0.24	0.428	0.06	0.22	0.415	0.058
	80	0.28	0.45	0.063	0.27	0.445	0.062	0.19	0.393	0.055
	90	0.345	0.477	0.066	0.23	0.422	0.059	0.245	0.431	0.06
	100	0.29	0.455	0.063	0.235	0.425	0.059	0.21	0.408	0.057

Table B.6: Target distance statistics: near primary target

	Size	$\omega = 0.5$ Min	Med	Max	$\omega = 1$ Min	Med	Max	$\omega = 3$ Min	Med	Max
$\eta = 1$	10	0.251	6.218	36.758	0.19	7.184	30.855	0.273	5.756	40.122
	20	0.258	10.325	109.187	0.398	10.413	110.378	0.455	9.832	89.234
	30	0.382	12.782	145.235	0.245	10.822	152.936	0.172	12.555	138.195
	40	0.093	18.912	129.448	0.172	14.34	130.312	0.074	18.176	162.723
	50	0.166	21.033	140.645	0.034	22.938	191.06	0.082	27.053	153.543
	60	0.083	33.916	156.705	0.209	24.394	172.431	0.557	32.798	156.267
	70	0.25	37.455	164.529	0.339	31.498	171.203	0.006	38.79	168.134
	80	0.215	37.353	168.05	0.245	36.367	170.879	0.179	39.935	178.845
	90	0.246	45.755	185.97	0.422	42.656	171.89	0.23	48.213	171.1
	100	0.161	39.294	186.302	0.259	46.451	164.746	0.636	53.721	188.169
$\eta = 2$	10	0.068	6.357	32.259	0.295	6.912	34.461	0.139	6.045	38.242
	20	0.126	8.77	90.378	0.214	9.144	88.472	0.201	9.218	72.98
	30	0.259	12.216	84.091	0.177	10.651	121.537	0.361	12.131	111.063
	40	0.142	13.343	139.026	0.21	19.512	168.605	0.074	13.916	118.73
	50	0.341	20.5	165.817	0.201	18.966	156.323	0.116	14.937	164.903
	60	0.293	24.473	179.261	0.352	22.007	150.498	0.337	30.339	165.329
	70	0.223	25.465	156.124	0.189	34.42	179.179	0.214	35.907	175.141
	80	0.318	41.847	172.896	0.388	33.656	162.52	0.375	38.925	173.974
	90	0.33	43.605	186.484	0.322	43.687	170.944	0.235	33.684	173.561
	100	0.498	44.931	171.201	0.172	44.567	174.603	0.431	49.877	187.039
$\eta = 5$	10	0.173	4.549	33.186	0.285	6.309	39.038	0.4	6.369	97.463
	20	0.074	8.602	111.305	0.021	9.381	96.638	0.118	10.793	88.51
	30	0.171	12.769	134.303	0.096	13.059	100.486	0.165	11.866	135.344
	40	0.363	12.028	116.153	0.545	17.812	103.439	0.116	16.552	137.492
	50	0.145	16.07	115.065	0.288	21.756	160.031	0.361	20.729	156.807
	60	0.201	20.108	175.284	0.34	19.703	139.988	0.457	33.703	177.778
	70	0.245	22.69	145.877	0.038	33.956	164.879	0.561	39.46	159.682
	80	0.125	32.529	186.275	0.319	45.224	172.365	0.348	35.486	184.27
	90	0.132	35.248	161.324	0.225	39.413	187.343	0.511	41.748	171.125
	100	0.215	40.577	168.351	0.223	47.29	185.369	0.366	51.606	163.926
$\eta = 20$	10	0.037	2.628	94.928	0.378	8.752	97.265	0.166	9.073	101.427
	20	0.25	9.726	93.772	0.183	18.703	103.278	0.107	22.774	114.094
	30	0.393	12.48	135.863	0.172	29.173	108.649	0.305	36.195	109.273
	40	0.233	16.098	116.883	0.082	28.925	167.197	0.268	38.417	113.134
	50	0.22	18.085	129.823	0.295	42.808	135.132	0.384	55.523	129.18
	60	0.176	26.198	163.821	0.211	49.285	163.857	0.153	46.858	142.624
	70	0.488	27.59	137.946	0.522	55.1	148.287	0.515	56.129	133.935
	80	0.549	30.005	186.988	0.4	51.62	182.103	0.454	61.193	169.562
	90	0.189	36.206	179.913	0.48	51.65	131.355	0.593	56.005	190.696
	100	0.243	44.61	185.147	0.436	59.337	186.227	0.614	59.385	181.675

Table B.7: Target distance statistics: from primary target

	Size	ω = 0.5 Mean	±SD	±CI	ω = 1 Mean	±SD	±CI	ω = 3 Mean	±SD	±CI
$\eta = 1$	10	0	0	0	0	0	0	0	0	0
	20	0	0	0	0	0	0	0.005	0.071	0.01
	30	0.005	0.071	0.01	0	0	0	0.005	0.071	0.01
	40	0.015	0.122	0.017	0.01	0.1	0.014	0	0	0
	50	0.005	0.071	0.01	0.01	0.1	0.014	0.005	0.071	0.01
	60	0.005	0.071	0.01	0.005	0.071	0.01	0.01	0.1	0.014
	70	0.005	0.071	0.01	0.01	0.1	0.014	0.015	0.122	0.017
	80	0.005	0.071	0.01	0.015	0.122	0.017	0.02	0.14	0.02
	90	0.01	0.1	0.014	0.015	0.122	0.017	0.02	0.14	0.02
	100	0.02	0.14	0.02	0.035	0.184	0.026	0.02	0.14	0.02
$\eta = 2$	10	0	0	0	0	0	0	0	0	0
	20	0	0	0	0	0	0	0	0	0
	30	0	0	0	0.02	0.14	0.02	0.015	0.122	0.017
	40	0	0	0	0.015	0.122	0.017	0	0	0
	50	0.005	0.071	0.01	0.005	0.071	0.01	0.005	0.071	0.01
	60	0.015	0.122	0.017	0.03	0.171	0.024	0.015	0.122	0.017
	70	0.025	0.157	0.022	0.03	0.171	0.024	0.04	0.196	0.027
	80	0.035	0.184	0.026	0.03	0.171	0.024	0.03	0.171	0.024
	90	0.015	0.122	0.017	0.02	0.14	0.02	0.04	0.196	0.027
	100	0.01	0.1	0.014	0.035	0.184	0.026	0.05	0.218	0.03
$\eta = 5$	10	0	0	0	0	0	0	0.015	0.122	0.017
	20	0	0	0	0.01	0.1	0.014	0	0	0
	30	0.01	0.1	0.014	0.04	0.196	0.027	0.04	0.196	0.027
	40	0.005	0.071	0.01	0.04	0.196	0.027	0.05	0.218	0.03
	50	0.035	0.184	0.026	0.04	0.196	0.027	0.025	0.157	0.022
	60	0.03	0.171	0.024	0.06	0.238	0.033	0.055	0.229	0.032
	70	0.01	0.1	0.014	0.065	0.247	0.034	0.075	0.264	0.037
	80	0.04	0.196	0.027	0.1	0.301	0.042	0.065	0.247	0.034
	90	0.035	0.184	0.026	0.06	0.238	0.033	0.08	0.272	0.038
	100	0.085	0.28	0.039	0.09	0.287	0.04	0.085	0.28	0.039
$\eta = 20$	10	0.005	0.071	0.01	0.025	0.157	0.022	0.08	0.272	0.038
	20	0	0	0	0.07	0.256	0.036	0.155	0.363	0.051
	30	0.015	0.122	0.017	0.165	0.372	0.052	0.185	0.389	0.054
	40	0.06	0.238	0.033	0.16	0.368	0.051	0.21	0.408	0.057
	50	0.065	0.247	0.034	0.205	0.405	0.056	0.285	0.453	0.063
	60	0.105	0.307	0.043	0.22	0.415	0.058	0.21	0.408	0.057
	70	0.065	0.247	0.034	0.285	0.453	0.063	0.335	0.473	0.066
	80	0.1	0.301	0.042	0.215	0.412	0.057	0.335	0.473	0.066
	90	0.09	0.287	0.04	0.215	0.412	0.057	0.25	0.434	0.061
	100	0.125	0.332	0.046	0.24	0.428	0.06	0.25	0.434	0.061

Table B.8: Target distance statistics: at secondary target

	Size	$\omega = 0.5$ Mean	±SD	±CI	$\omega = 1$ Mean	±SD	±CI	$\omega = 3$ Mean	±SD	±CI
$\eta = 1$	10	0	0	0	0	0	0	0	0	0
	20	0.02	0.14	0.02	0.02	0.14	0.02	0.005	0.071	0.01
	30	0.035	0.184	0.026	0.045	0.208	0.029	0.045	0.208	0.029
	40	0.045	0.208	0.029	0.09	0.287	0.04	0.065	0.247	0.034
	50	0.11	0.314	0.044	0.08	0.272	0.038	0.105	0.307	0.043
	60	0.115	0.32	0.045	0.075	0.264	0.037	0.08	0.272	0.038
	70	0.155	0.363	0.051	0.11	0.314	0.044	0.11	0.314	0.044
	80	0.11	0.314	0.044	0.08	0.272	0.038	0.045	0.208	0.029
	90	0.11	0.314	0.044	0.135	0.343	0.048	0.14	0.348	0.049
	100	0.11	0.314	0.044	0.115	0.32	0.045	0.145	0.353	0.049
$\eta = 2$	10	0	0	0	0	0	0	0	0	0
	20	0.025	0.157	0.022	0.005	0.071	0.01	0.035	0.184	0.026
	30	0.05	0.218	0.03	0.025	0.157	0.022	0.05	0.218	0.03
	40	0.105	0.307	0.043	0.085	0.28	0.039	0.055	0.229	0.032
	50	0.125	0.332	0.046	0.09	0.287	0.04	0.07	0.256	0.036
	60	0.115	0.32	0.045	0.1	0.301	0.042	0.145	0.353	0.049
	70	0.13	0.337	0.047	0.155	0.363	0.051	0.1	0.301	0.042
	80	0.14	0.348	0.049	0.145	0.353	0.049	0.135	0.343	0.048
	90	0.115	0.32	0.045	0.15	0.358	0.05	0.07	0.256	0.036
	100	0.145	0.353	0.049	0.155	0.363	0.051	0.135	0.343	0.048
$\eta = 5$	10	0	0	0	0	0	0	0.005	0.071	0.01
	20	0.025	0.157	0.022	0.015	0.122	0.017	0.06	0.238	0.033
	30	0.065	0.247	0.034	0.095	0.294	0.041	0.085	0.28	0.039
	40	0.11	0.314	0.044	0.15	0.358	0.05	0.155	0.363	0.051
	50	0.13	0.337	0.047	0.17	0.377	0.053	0.145	0.353	0.049
	60	0.165	0.372	0.052	0.135	0.343	0.048	0.235	0.425	0.059
	70	0.135	0.343	0.048	0.22	0.415	0.058	0.2	0.401	0.056
	80	0.19	0.393	0.055	0.245	0.431	0.06	0.165	0.372	0.052
	90	0.19	0.393	0.055	0.205	0.405	0.056	0.215	0.412	0.057
	100	0.165	0.372	0.052	0.21	0.408	0.057	0.21	0.408	0.057
$\eta = 20$	10	0.01	0.1	0.014	0.04	0.196	0.027	0.075	0.264	0.037
	20	0.04	0.196	0.027	0.15	0.358	0.05	0.17	0.377	0.053
	30	0.055	0.229	0.032	0.21	0.408	0.057	0.26	0.44	0.061
	40	0.165	0.372	0.052	0.22	0.415	0.058	0.255	0.437	0.061
	50	0.22	0.415	0.058	0.28	0.45	0.063	0.27	0.445	0.062
	60	0.165	0.372	0.052	0.295	0.457	0.064	0.31	0.464	0.065
	70	0.255	0.437	0.061	0.245	0.431	0.06	0.26	0.44	0.061
	80	0.24	0.428	0.06	0.235	0.425	0.059	0.27	0.445	0.062
	90	0.205	0.405	0.056	0.27	0.445	0.062	0.215	0.412	0.057
	100	0.21	0.408	0.057	0.28	0.45	0.063	0.32	0.468	0.065

Table B.9: Target distance statistics: near secondary target

	Size	$\omega = 0.5$ Min	Med	Max	$\omega = 1$ Min	Med	Max	$\omega = 3$ Min	Med	Max
$\eta = 1$	10	62.568	94.117	110.597	64.828	95.758	114.929	67.038	97.313	122.104
	20	17.022	91.131	114.907	23.307	95.015	124.196	8.148	97.518	116.783
	30	4.829	84.671	141.99	14.672	91.171	189.274	8.926	91.297	155.989
	40	0.535	85.738	158.575	4.66	89.2	156.32	20.008	91.719	187.295
	50	0.351	81.173	145.168	0.711	83.837	169.174	9.006	88.449	166.991
	60	2.632	82.15	159.292	7.153	87.125	163.917	0.894	88.4	169.523
	70	3.94	79.438	188.566	0.999	84.833	179.334	1.04	89.378	183.547
	80	2.118	80.041	148.979	5.528	84.965	188.216	1.32	86.394	158.784
	90	1.08	82.514	183.726	0.725	78.38	188.38	0.481	84.998	180.227
	100	0.771	76.954	186.711	0.713	82.374	164.448	1.179	81.965	167.524
$\eta = 2$	10	65.962	93.079	118.536	63.029	95.216	117.318	61.304	97.984	121.999
	20	11.323	91.695	120.458	47.901	95.828	122.074	24.316	94.279	116.445
	30	10.733	87.882	112.629	0.687	91.821	161.937	4.969	92.39	126.464
	40	9.729	87.017	143.793	3.812	83.69	167.47	14.35	87.668	131.496
	50	8.062	80.891	171.625	2.763	84.874	149.994	0.88	84.319	166.599
	60	2.88	78.365	161.043	0.579	81.245	168.308	0.463	82.296	184.805
	70	1.148	75.782	145.258	0.495	75.98	169.412	0.924	86.736	167.005
	80	0.809	78.061	172.296	0.617	79.307	169.824	0.336	81.496	158.592
	90	4.165	84.237	179.547	1.025	83.052	172.682	0.472	80.6	185.147
	100	4.065	74.524	166.503	0.393	82.39	172.586	0.316	75.899	180.299
$\eta = 5$	10	64.759	94.535	117.179	55.797	95.98	118.739	1.699	96.444	119.104
	20	17.488	89.484	114.463	0.826	91.275	116.023	14.373	91.423	115.511
	30	4.933	86.414	170.032	0.237	84.191	119.516	0.427	90.606	122.572
	40	6.742	83.102	114.122	0.646	78.487	120.178	1.169	78.032	170.122
	50	0.956	79.84	133.403	0.311	72.038	145.72	0.427	79.297	168.32
	60	0.721	75.573	178.718	0.107	72.687	173.994	0.326	71.105	159.54
	70	3.559	74.061	159.313	0.758	66.27	161.387	0.521	69.428	182.614
	80	0.274	71.023	173.218	0.266	60.163	176.199	0.366	76.521	182.252
	90	0.637	73.6	171.793	0.319	69.998	161.174	0.153	64.703	174.782
	100	0.321	74.552	166.849	0.241	65.917	184.181	0.356	65.547	181.524
$\eta = 20$	10	3.363	95.719	106.451	1.154	94.506	119.72	0.605	94.298	115.591
	20	14.736	87.624	113.745	0.866	77.511	111.469	0.215	70.7	115.254
	30	1.564	82.665	114.394	0.497	62.392	111.003	0.185	52.717	114.989
	40	0.898	72.721	116.549	0.088	56.911	139.497	0.324	47.594	129.946
	50	0.167	69.154	136.131	0.259	42.708	157.328	0.164	34.385	149.338
	60	0.506	70.564	170.304	0.154	40.788	165.018	0.213	38.602	156.491
	70	0.664	61.74	156.076	0.379	36.784	123.039	0.347	29.43	174.738
	80	0.54	63.73	172.925	0.556	49.895	177.41	0.065	27.906	158.653
	90	0.48	63.118	181.857	0.507	43.626	139.55	0.162	43.356	178.215
	100	0.366	56.874	177.916	0.296	39.626	154.704	0.151	35.873	171.192

Table B.10: Target distance statistics: from secondary target

	Size	$\omega = 0.5$ Min	Med	Max	$\omega = 1$ Min	Med	Max	$\omega = 3$ Min	Med	Max
$\eta = 1$	10	63.335	95.103	112.327	0.064	1.858	108.734	0.064	1.501	101.146
	20	21.965	94.43	122.805	0.137	1.544	120.667	0.166	1.579	115.247
	30	12.822	88.144	156.512	0.037	2.084	132.33	0.145	1.590	118.481
	40	5.45	91.085	162.321	0.077	1.676	105.764	0.116	1.612	105.949
	50	12.585	87.385	145.168	0.11	1.807	130.27	0.095	1.667	113.229
	60	12.483	87.925	176.041	0.162	2.205	162.52	0.125	1.662	112.514
	70	14.638	85.523	198.392	0.124	2.629	170.018	0.081	1.619	115.059
	80	14.204	87.703	169.436	0.02	4.812	125.646	0.07	1.852	109.971
	90	7.505	89.806	187.766	0.211	4.328	160.664	0.19	1.486	121.971
	100	5.797	85.74	200.725	0.152	12.113	155.607	0.076	1.730	117.627
$\eta = 2$	10	67.861	94.058	119.346	0.143	3.05	112.589	0.195	1.874	112.274
	20	16.439	93.706	125.204	0.046	1.817	119.657	0.227	1.606	118.999
	30	17.813	91.675	122.294	0.276	1.904	117.597	0.024	1.784	117.978
	40	12.603	91.828	147.233	0.046	2.343	115.211	0.086	1.833	118.393
	50	11.522	88.831	172.988	0.138	2.144	135.451	0.154	1.692	109.6
	60	6.053	85.308	172.434	0.173	2.117	144.263	0.054	1.856	106.059
	70	1.041	83.225	153.591	0.08	8.101	172.379	0.093	1.778	123.734
	80	1.311	87.133	172.296	0.068	19.06	139.867	0.235	2.17	159.781
	90	12.313	91.207	177.141	0.274	20.51	182.401	0.122	1.969	153.986
	100	9.215	84.197	170.164	0.083	17.498	144.403	0.093	2.17	185.955
$\eta = 5$	10	67.229	96.017	119.566	0.144	7.544	109.464	0.08	2.483	104.723
	20	23.998	92.487	123.064	0.213	25.447	117.91	0.133	2.151	118.954
	30	17.846	90.183	123.112	0.069	31.336	120.402	0.039	2.967	118.564
	40	11.766	90.856	122.133	0.143	22.137	128.279	0.209	3.045	117.2
	50	3.55	84.769	133.403	0.062	27.23	121.151	0.192	3.598	119.441
	60	3.344	81.721	183.413	0.238	31.209	130.614	0.196	4.784	136.323
	70	13.632	82.334	199.767	0.108	30.327	131.518	0.15	8.686	136.3
	80	3.564	76.403	195.528	0.186	24.831	186.977	0.05	4.381	146.006
	90	2.147	81.654	188.768	0.184	45.352	166.197	0.214	13.396	167.328
	100	3.349	81.84	160.242	0.2	36.354	167.566	0.165	13.877	150.307
$\eta = 20$	10	3.251	96.582	108.7	0.052	3.472	116.145	0.137	1.853	100.598
	20	19.24	92.208	117.876	0.171	58.901	108.664	0.178	14.29	113.844
	30	7.753	87.838	120.596	0.057	42.305	117.404	0.254	24.395	120.753
	40	2.248	81.02	119.399	0.349	52.207	120.475	0.549	29.352	121.496
	50	1.66	75.649	145.837	0.568	35.541	131.94	0.559	21.773	122.601
	60	8.313	72.334	160.828	0.749	33.173	121.945	0.36	27.114	126.033
	70	3.415	65.422	169.757	1.053	33.855	124.121	1.407	19.747	113.361
	80	8.367	68.359	190.45	0.778	35.291	199.259	1.096	21.147	133.938
	90	5.84	64.631	165.238	2.177	41.785	130.476	0.885	25.283	123.967
	100	3.193	55.062	169.392	1.289	26.521	134.771	1.813	23.629	124.14

Table B.11: Target distance statistics: intruder from his target

B.4 Intruder Group Size

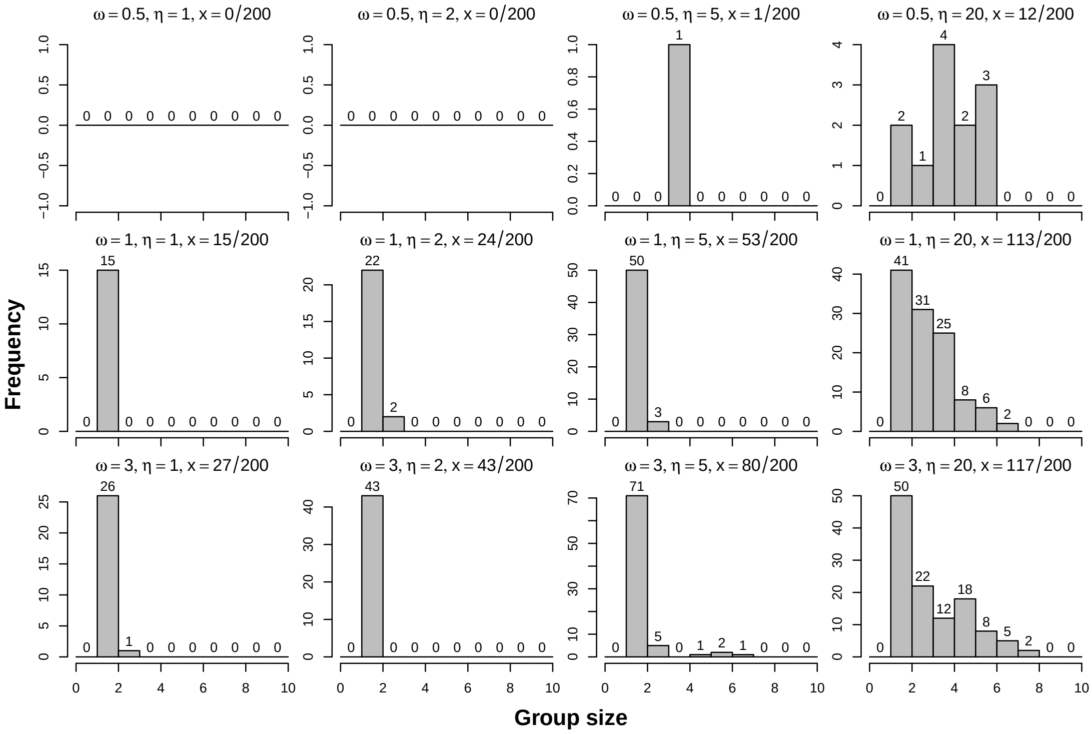

Figure B.3: Intruder group size comparison, $N = 10$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\omega = 0.5$	$\eta = 1$	0	0	0	0	0	0	1	0	0
	$\eta = 2$	0	0	0	0	0	0	1	0	0
	$\eta = 5$	0	0	0	0.005	0.071	0.01	0.995	0.071	0.01
	$\eta = 20$	0	0	0	0.06	0.238	0.033	0.94	0.238	0.033
$\omega = 1$	$\eta = 1$	0.79	0.408	0.057	0.075	0.264	0.037	0.135	0.343	0.048
	$\eta = 2$	0.65	0.478	0.067	0.12	0.326	0.045	0.23	0.422	0.059
	$\eta = 5$	0.52	0.501	0.07	0.265	0.442	0.062	0.215	0.412	0.057
	$\eta = 20$	0.25	0.434	0.061	0.565	0.497	0.069	0.185	0.389	0.054
$\omega = 3$	$\eta = 1$	0.825	0.381	0.053	0.135	0.343	0.048	0.04	0.196	0.027
	$\eta = 2$	0.72	0.45	0.063	0.215	0.412	0.057	0.065	0.247	0.034
	$\eta = 5$	0.48	0.501	0.07	0.4	0.491	0.068	0.12	0.326	0.045
	$\eta = 20$	0.3	0.459	0.064	0.585	0.494	0.069	0.115	0.32	0.045

Table B.12: Intruder group size statistics, $N = 10$

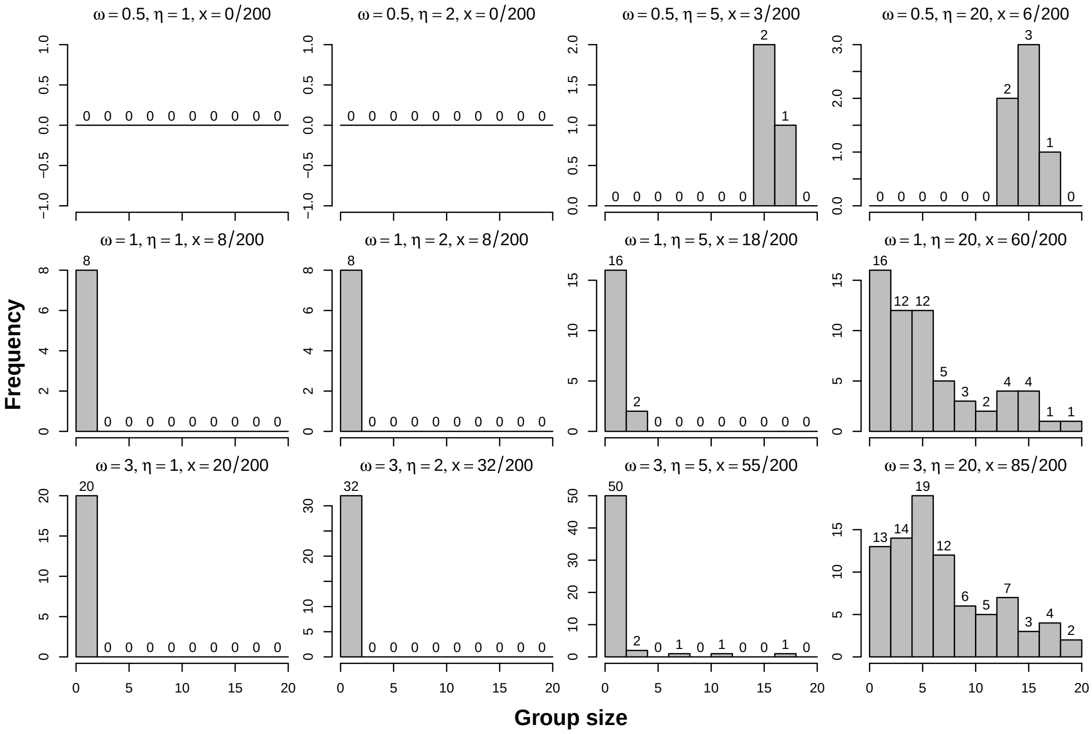

Figure B.4: Intruder group size comparison, $N = 20$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\omega = 0.5$	$\eta = 1$	0.005	0.071	0.01	0	0	0	0.995	0.071	0.01
	$\eta = 2$	0	0	0	0	0	0	1	0	0
	$\eta = 5$	0.005	0.071	0.01	0.015	0.122	0.017	0.98	0.14	0.02
	$\eta = 20$	0	0	0	0.03	0.171	0.024	0.97	0.171	0.024
$\omega = 1$	$\eta = 1$	0.755	0.431	0.06	0.04	0.196	0.027	0.205	0.405	0.056
	$\eta = 2$	0.72	0.45	0.063	0.04	0.196	0.027	0.24	0.428	0.06
	$\eta = 5$	0.565	0.497	0.069	0.09	0.287	0.04	0.345	0.477	0.066
	$\eta = 20$	0.055	0.229	0.032	0.295	0.457	0.064	0.645	0.48	0.067
$\omega = 3$	$\eta = 1$	0.86	0.348	0.049	0.1	0.301	0.042	0.04	0.196	0.027
	$\eta = 2$	0.75	0.434	0.061	0.16	0.368	0.051	0.09	0.287	0.04
	$\eta = 5$	0.535	0.5	0.07	0.275	0.448	0.062	0.19	0.393	0.055
	$\eta = 20$	0.085	0.28	0.039	0.415	0.494	0.069	0.49	0.501	0.07

Table B.13: Intruder group size statistics, $N = 20$

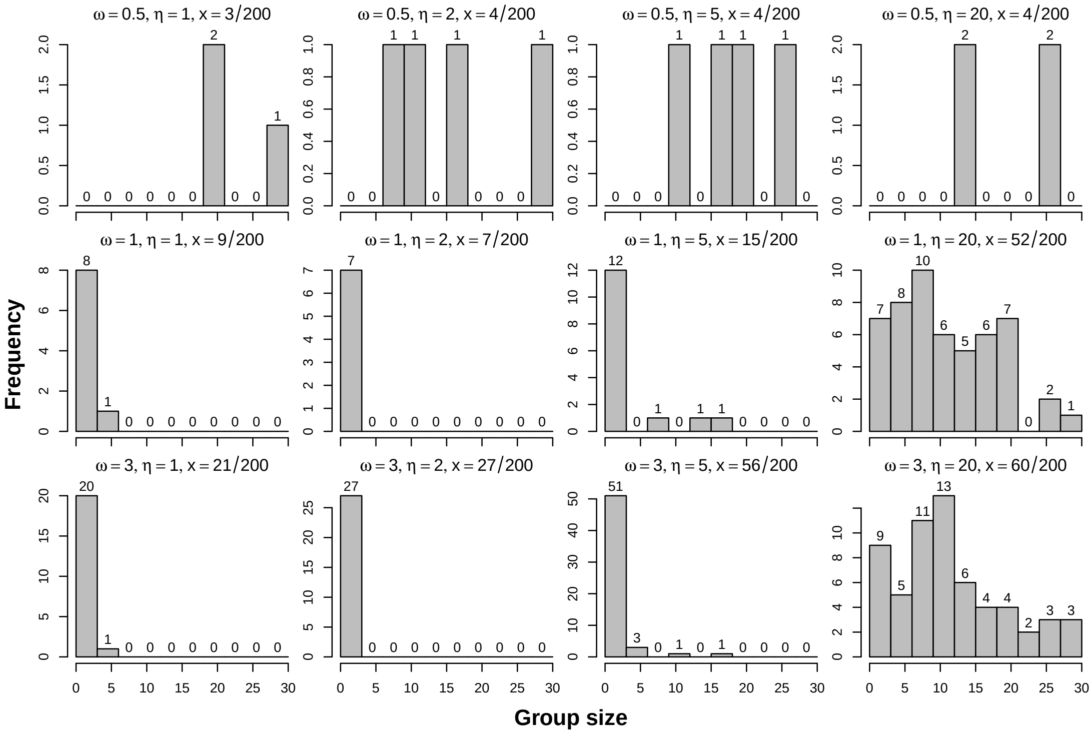

Figure B.5: Intruder group size comparison, $N = 30$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\omega = 0.5$	$\eta = 1$	0	0	0	0.01	0.1	0.014	0.985	0.122	0.017
	$\eta = 2$	0	0	0	0.015	0.122	0.017	0.98	0.14	0.02
	$\eta = 5$	0	0	0	0.02	0.14	0.02	0.98	0.14	0.02
	$\eta = 20$	0	0	0	0.02	0.14	0.02	0.98	0.14	0.02
$\omega = 1$	$\eta = 1$	0.675	0.47	0.065	0.045	0.208	0.029	0.28	0.45	0.063
	$\eta = 2$	0.69	0.464	0.065	0.035	0.184	0.026	0.275	0.448	0.062
	$\eta = 5$	0.475	0.501	0.07	0.075	0.264	0.037	0.45	0.499	0.07
	$\eta = 20$	0.01	0.1	0.014	0.255	0.437	0.061	0.73	0.445	0.062
$\omega = 3$	$\eta = 1$	0.8	0.401	0.056	0.105	0.307	0.043	0.095	0.294	0.041
	$\eta = 2$	0.735	0.442	0.062	0.135	0.343	0.048	0.13	0.337	0.047
	$\eta = 5$	0.46	0.5	0.07	0.28	0.45	0.063	0.26	0.44	0.061
	$\eta = 20$	0.035	0.184	0.026	0.29	0.455	0.063	0.665	0.473	0.066

Table B.14: Intruder group size statistics, $N = 30$

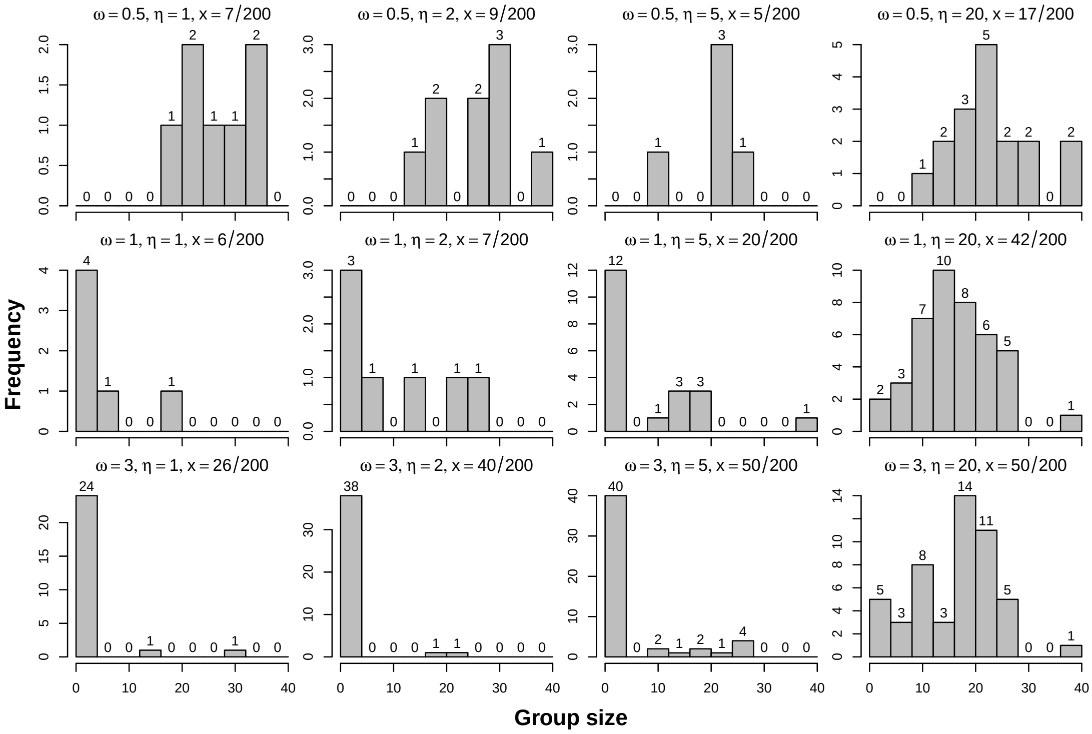

Figure B.6: Intruder group size comparison, $N = 40$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\boldsymbol{\omega = 0.5}$	$\boldsymbol{\eta = 1}$	0	0	0	0.035	0.184	0.026	0.965	0.184	0.026
	$\boldsymbol{\eta = 2}$	0	0	0	0.04	0.196	0.027	0.955	0.208	0.029
	$\boldsymbol{\eta = 5}$	0	0	0	0.025	0.157	0.022	0.975	0.157	0.022
	$\boldsymbol{\eta = 20}$	0	0	0	0.085	0.28	0.039	0.915	0.28	0.039
$\boldsymbol{\omega = 1}$	$\boldsymbol{\eta = 1}$	0.715	0.453	0.063	0.03	0.171	0.024	0.255	0.437	0.061
	$\boldsymbol{\eta = 2}$	0.69	0.464	0.065	0.035	0.184	0.026	0.275	0.448	0.062
	$\boldsymbol{\eta = 5}$	0.425	0.496	0.069	0.095	0.294	0.041	0.475	0.501	0.07
	$\boldsymbol{\eta = 20}$	0	0	0	0.205	0.405	0.056	0.79	0.408	0.057
$\boldsymbol{\omega = 3}$	$\boldsymbol{\eta = 1}$	0.795	0.405	0.056	0.13	0.337	0.047	0.075	0.264	0.037
	$\boldsymbol{\eta = 2}$	0.68	0.468	0.065	0.2	0.401	0.056	0.12	0.326	0.045
	$\boldsymbol{\eta = 5}$	0.495	0.501	0.07	0.25	0.434	0.061	0.255	0.437	0.061
	$\boldsymbol{\eta = 20}$	0.02	0.14	0.02	0.25	0.434	0.061	0.73	0.445	0.062

Table B.15: Intruder group size statistics, $N = 40$

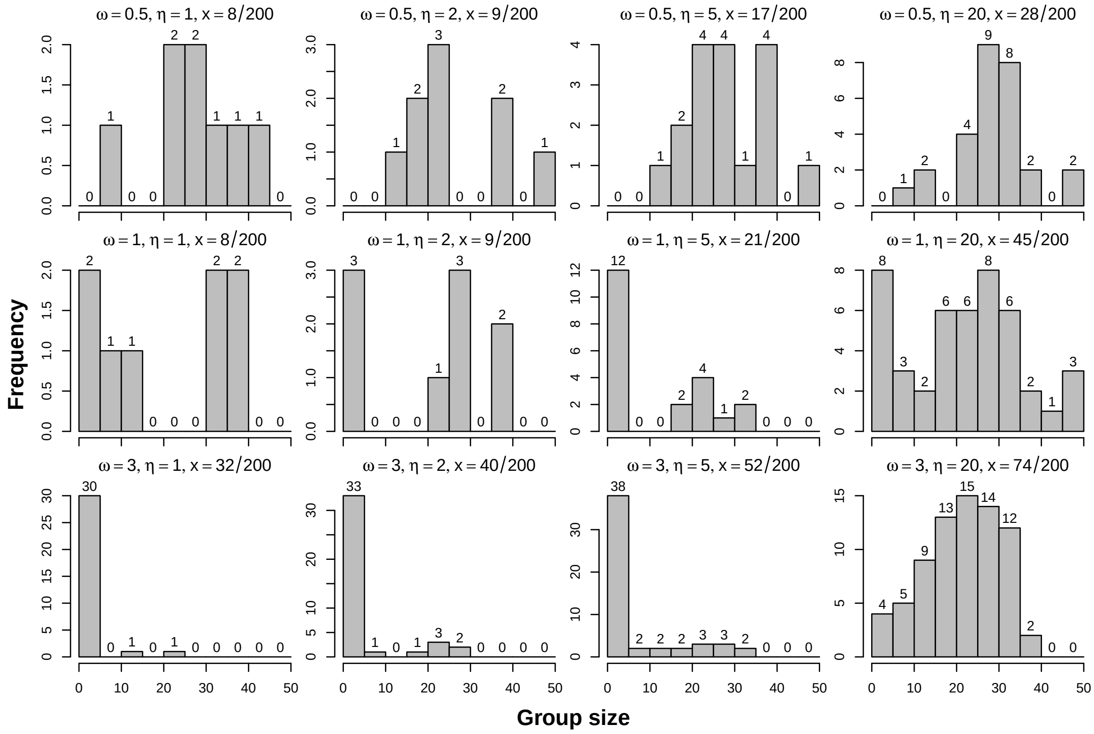

Figure B.7: Intruder group size comparison, $N = 50$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\boldsymbol{\omega = 0.5}$	$\boldsymbol{\eta = 1}$	0	0	0	0.04	0.196	0.027	0.96	0.196	0.027
	$\boldsymbol{\eta = 2}$	0	0	0	0.04	0.196	0.027	0.955	0.208	0.029
	$\boldsymbol{\eta = 5}$	0.005	0.071	0.010	0.085	0.28	0.039	0.91	0.287	0.04
	$\boldsymbol{\eta = 20}$	0	0	0	0.13	0.337	0.047	0.86	0.348	0.049
$\boldsymbol{\omega = 1}$	$\boldsymbol{\eta = 1}$	0.735	0.442	0.062	0.04	0.196	0.027	0.225	0.419	0.058
	$\boldsymbol{\eta = 2}$	0.66	0.475	0.066	0.045	0.208	0.029	0.295	0.457	0.064
	$\boldsymbol{\eta = 5}$	0.395	0.49	0.068	0.105	0.307	0.043	0.5	0.501	0.07
	$\boldsymbol{\eta = 20}$	0	0	0	0.22	0.415	0.058	0.775	0.419	0.058
$\boldsymbol{\omega = 3}$	$\boldsymbol{\eta = 1}$	0.78	0.415	0.058	0.16	0.368	0.051	0.06	0.238	0.033
	$\boldsymbol{\eta = 2}$	0.68	0.468	0.065	0.2	0.401	0.056	0.12	0.326	0.045
	$\boldsymbol{\eta = 5}$	0.475	0.501	0.07	0.26	0.44	0.061	0.265	0.442	0.062
	$\boldsymbol{\eta = 20}$	0	0	0	0.37	0.484	0.067	0.63	0.484	0.067

Table B.16: Intruder group size statistics, $N = 50$

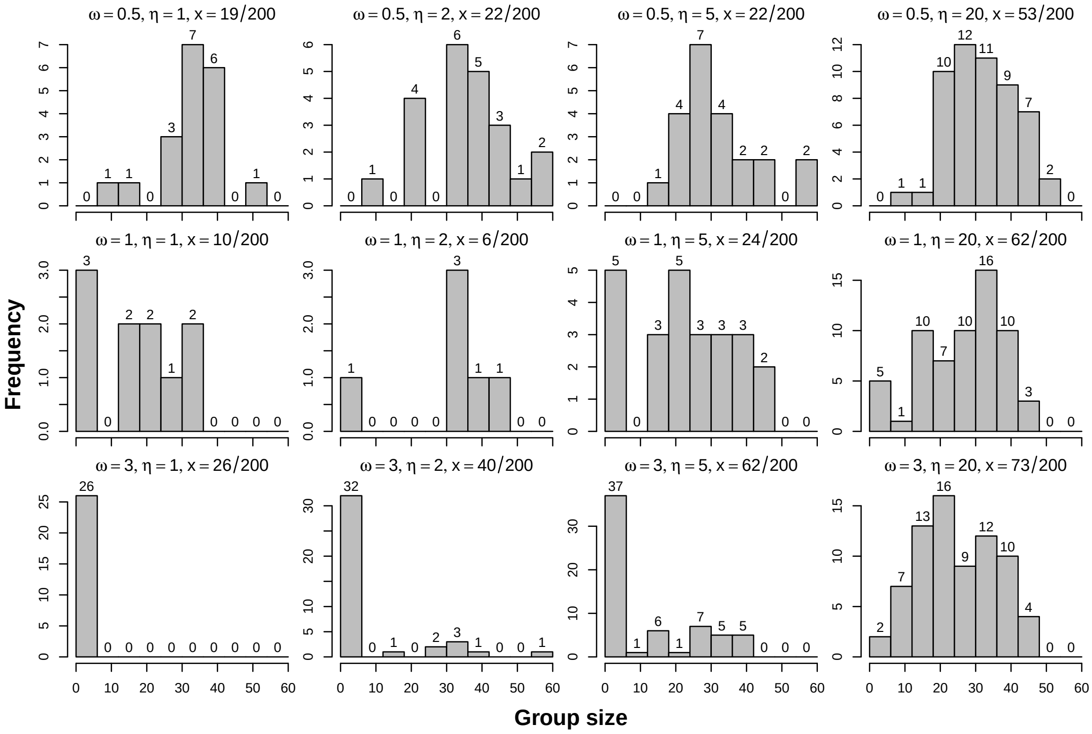

Figure B.8: Intruder group size comparison, $N = 60$

		Alone Mean	*Alone* ±SD	*Alone* ±CI	*In Group* Mean	*In Group* ±SD	*In Group* ±CI	*No Frag.* Mean	*No Frag.* ±SD	*No Frag.* ±CI
$\omega = 0.5$	$\eta = 1$	0	0	0	0.095	0.294	0.041	0.905	0.294	0.041
	$\eta = 2$	0	0	0	0.11	0.314	0.044	0.89	0.314	0.044
	$\eta = 5$	0	0	0	0.105	0.307	0.043	0.89	0.314	0.044
	$\eta = 20$	0	0	0	0.265	0.442	0.062	0.735	0.442	0.062
$\omega = 1$	$\eta = 1$	0.7	0.459	0.064	0.05	0.218	0.03	0.25	0.434	0.061
	$\eta = 2$	0.7	0.459	0.064	0.03	0.171	0.024	0.27	0.445	0.062
	$\eta = 5$	0.355	0.48	0.067	0.12	0.326	0.045	0.525	0.501	0.07
	$\eta = 20$	0	0	0	0.31	0.464	0.065	0.69	0.464	0.065
$\omega = 3$	$\eta = 1$	0.765	0.425	0.059	0.13	0.337	0.047	0.105	0.307	0.043
	$\eta = 2$	0.66	0.475	0.066	0.2	0.401	0.056	0.14	0.348	0.049
	$\eta = 5$	0.45	0.499	0.07	0.31	0.464	0.065	0.24	0.428	0.06
	$\eta = 20$	0.005	0.071	0.01	0.365	0.483	0.067	0.63	0.484	0.067

Table B.17: Intruder group size statistics, $N = 60$

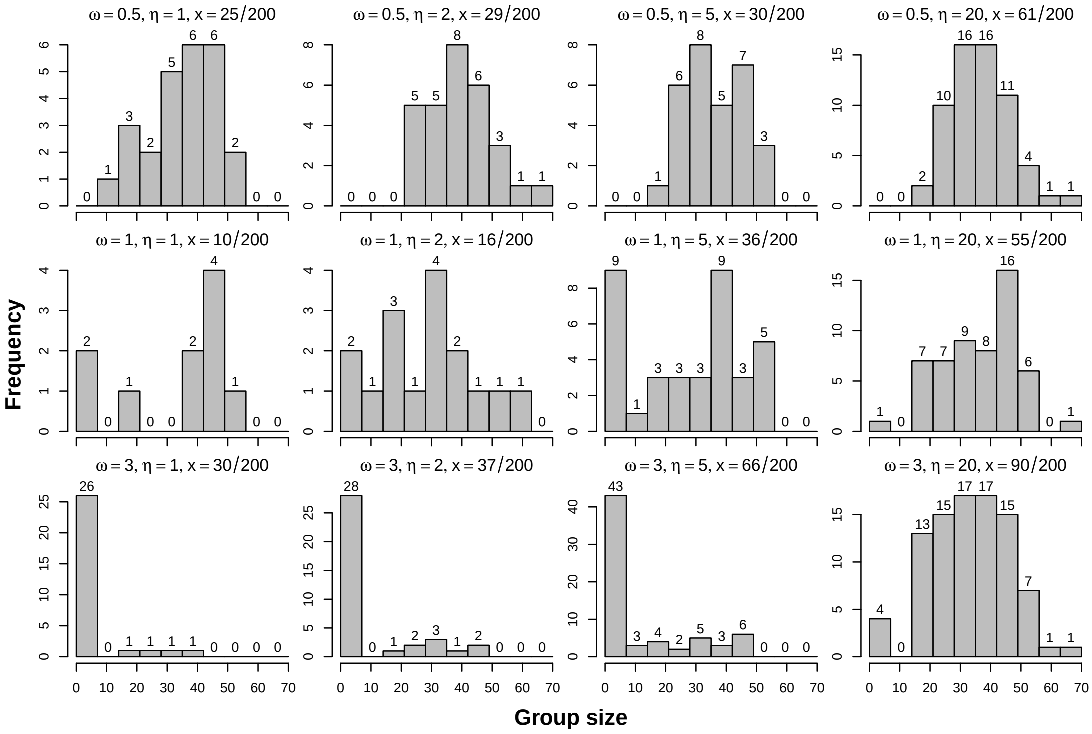

Figure B.9: Intruder group size comparison, $N = 70$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\boldsymbol{\omega = 0.5}$	$\boldsymbol{\eta = 1}$	0	0	0	0.125	0.332	0.046	0.875	0.332	0.046
	$\boldsymbol{\eta = 2}$	0.005	0.071	0.01	0.145	0.353	0.049	0.85	0.358	0.05
	$\boldsymbol{\eta = 5}$	0	0	0	0.15	0.358	0.05	0.85	0.358	0.05
	$\boldsymbol{\eta = 20}$	0	0	0	0.3	0.459	0.064	0.695	0.462	0.064
$\boldsymbol{\omega = 1}$	$\boldsymbol{\eta = 1}$	0.69	0.464	0.065	0.05	0.218	0.03	0.26	0.44	0.061
	$\boldsymbol{\eta = 2}$	0.605	0.49	0.068	0.08	0.272	0.038	0.315	0.466	0.065
	$\boldsymbol{\eta = 5}$	0.33	0.471	0.066	0.18	0.385	0.054	0.49	0.501	0.07
	$\boldsymbol{\eta = 20}$	0.005	0.071	0.01	0.27	0.445	0.062	0.72	0.45	0.063
$\boldsymbol{\omega = 3}$	$\boldsymbol{\eta = 1}$	0.725	0.448	0.062	0.15	0.358	0.05	0.125	0.332	0.046
	$\boldsymbol{\eta = 2}$	0.69	0.464	0.065	0.185	0.389	0.054	0.125	0.332	0.046
	$\boldsymbol{\eta = 5}$	0.395	0.49	0.068	0.33	0.471	0.066	0.275	0.448	0.062
	$\boldsymbol{\eta = 20}$	0.005	0.071	0.01	0.45	0.499	0.07	0.545	0.499	0.07

Table B.18: Intruder group size statistics, $N = 70$

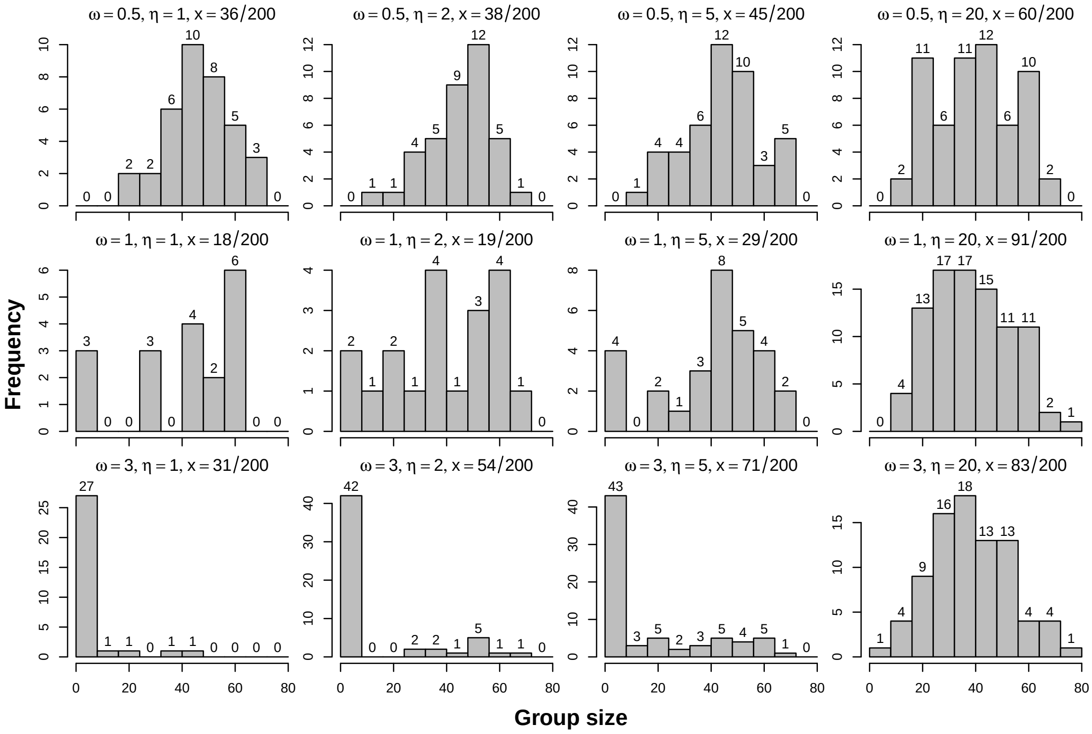

Figure B.10: Intruder group size comparison, $N = 80$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\boldsymbol{\omega = 0.5}$	$\boldsymbol{\eta = 1}$	0.005	0.071	0.01	0.18	0.385	0.054	0.815	0.389	0.054
	$\boldsymbol{\eta = 2}$	0	0	0	0.19	0.393	0.055	0.81	0.393	0.055
	$\boldsymbol{\eta = 5}$	0	0	0	0.225	0.419	0.058	0.775	0.419	0.058
	$\boldsymbol{\eta = 20}$	0	0	0	0.3	0.459	0.064	0.7	0.459	0.064
$\boldsymbol{\omega = 1}$	$\boldsymbol{\eta = 1}$	0.665	0.473	0.066	0.09	0.287	0.04	0.245	0.431	0.06
	$\boldsymbol{\eta = 2}$	0.545	0.499	0.07	0.095	0.294	0.041	0.36	0.481	0.067
	$\boldsymbol{\eta = 5}$	0.36	0.481	0.067	0.145	0.353	0.049	0.495	0.501	0.07
	$\boldsymbol{\eta = 20}$	0	0	0	0.455	0.499	0.07	0.545	0.499	0.07
$\boldsymbol{\omega = 3}$	$\boldsymbol{\eta = 1}$	0.73	0.445	0.062	0.155	0.363	0.051	0.115	0.32	0.045
	$\boldsymbol{\eta = 2}$	0.62	0.487	0.068	0.27	0.445	0.062	0.11	0.314	0.044
	$\boldsymbol{\eta = 5}$	0.4	0.491	0.068	0.355	0.48	0.067	0.245	0.431	0.06
	$\boldsymbol{\eta = 20}$	0.005	0.071	0.01	0.41	0.493	0.069	0.58	0.495	0.069

Table B.19: Intruder group size statistics, $N = 80$

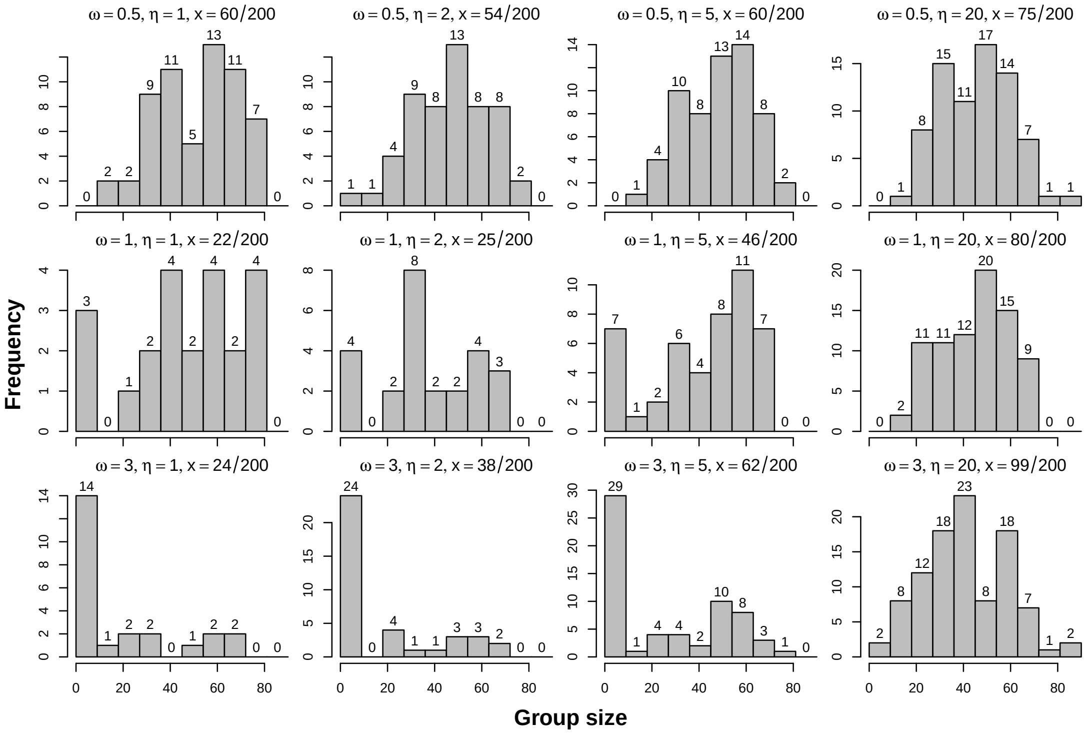

Figure B.11: Intruder group size comparison, $N = 90$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\boldsymbol{\omega = 0.5}$	$\boldsymbol{\eta = 1}$	0	0	0	0.3	0.459	0.064	0.7	0.459	0.064
	$\boldsymbol{\eta = 2}$	0	0	0	0.27	0.445	0.062	0.73	0.445	0.062
	$\boldsymbol{\eta = 5}$	0	0	0	0.3	0.459	0.064	0.7	0.459	0.064
	$\boldsymbol{\eta = 20}$	0	0	0	0.375	0.485	0.068	0.625	0.485	0.068
$\boldsymbol{\omega = 1}$	$\boldsymbol{\eta = 1}$	0.635	0.483	0.067	0.11	0.314	0.044	0.255	0.437	0.061
	$\boldsymbol{\eta = 2}$	0.55	0.499	0.07	0.125	0.332	0.046	0.325	0.47	0.065
	$\boldsymbol{\eta = 5}$	0.3	0.459	0.064	0.23	0.422	0.059	0.47	0.5	0.07
	$\boldsymbol{\eta = 20}$	0	0	0	0.4	0.491	0.068	0.6	0.491	0.068
$\boldsymbol{\omega = 3}$	$\boldsymbol{\eta = 1}$	0.79	0.408	0.057	0.12	0.326	0.045	0.090	0.287	0.04
	$\boldsymbol{\eta = 2}$	0.66	0.475	0.066	0.190	0.393	0.055	0.15	0.358	0.05
	$\boldsymbol{\eta = 5}$	0.365	0.483	0.067	0.31	0.464	0.065	0.325	0.47	0.065
	$\boldsymbol{\eta = 20}$	0.005	0.071	0.01	0.495	0.501	0.07	0.5	0.501	0.07

Table B.20: Intruder group size statistics, $N = 90$

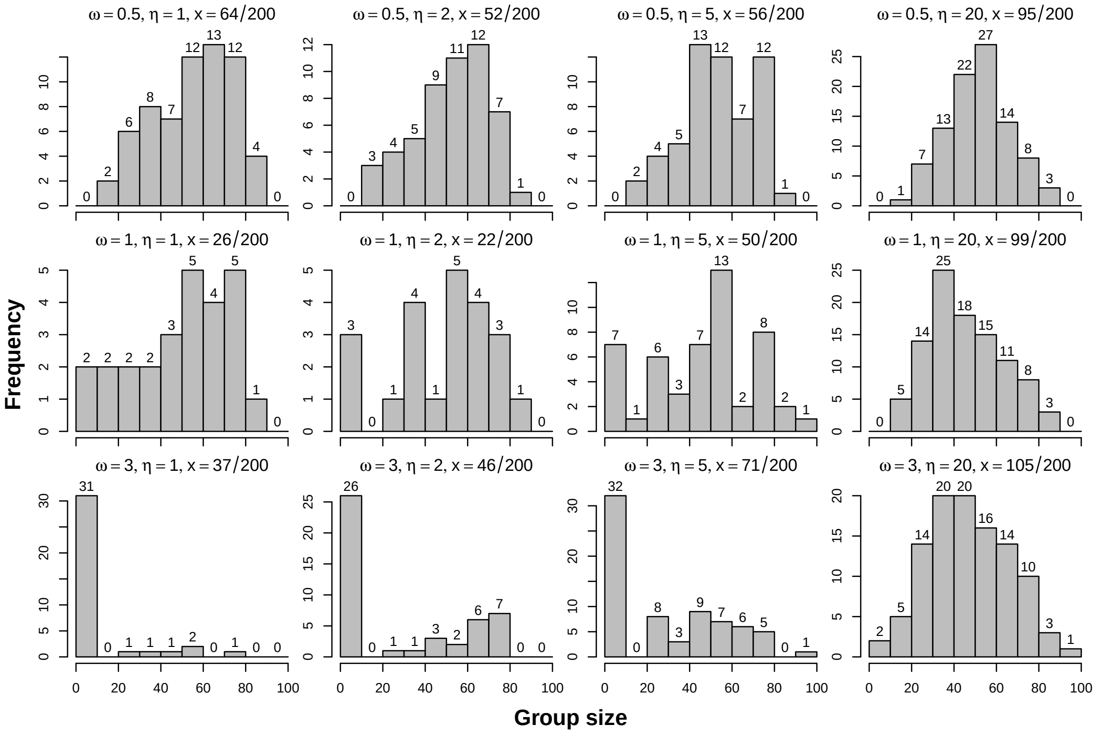

Figure B.12: Intruder group size comparison, $N = 100$

		Alone			***In Group***			***No Frag.***		
		Mean	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**	**Mean**	**±SD**	**±CI**
$\omega = 0.5$	$\eta = 1$	0	0	0	0.32	0.468	0.065	0.68	0.468	0.065
	$\eta = 2$	0	0	0	0.26	0.44	0.061	0.74	0.44	0.061
	$\eta = 5$	0	0	0	0.28	0.45	0.063	0.72	0.45	0.063
	$\eta = 20$	0	0	0	0.475	0.501	0.07	0.525	0.501	0.07
$\omega = 1$	$\eta = 1$	0.645	0.48	0.067	0.13	0.337	0.047	0.225	0.419	0.058
	$\eta = 2$	0.575	0.496	0.069	0.11	0.314	0.044	0.315	0.466	0.065
	$\eta = 5$	0.265	0.442	0.062	0.245	0.431	0.06	0.485	0.501	0.07
	$\eta = 20$	0	0	0	0.495	0.501	0.07	0.505	0.501	0.07
$\omega = 3$	$\eta = 1$	0.72	0.45	0.063	0.185	0.389	0.054	0.095	0.294	0.041
	$\eta = 2$	0.625	0.485	0.068	0.23	0.422	0.059	0.145	0.353	0.049
	$\eta = 5$	0.35	0.478	0.067	0.355	0.48	0.067	0.295	0.457	0.064
	$\eta = 20$	0.005	0.071	0.01	0.525	0.501	0.07	0.47	0.5	0.07

Table B.21: Intruder group size statistics, $N = 100$

C. DVD Contents

The structure and description of supplementary materials on accompanied DVD (**bold** denotes folder, *slanted* denotes file):

- **docs** – Additional documents.
  - *prog_guide.pdf* – Programmer Guide for Muragatte toolset.
  - *user_manual.pdf* – User Manual for Muragatte toolset.
- **experiments** – The results of our experiments.
  - **data** – Results of experiments used for thesis.
    - **Completed** – Saved experiments with their histories. Empty.
    - **Experiments** – The settings for all experiments.
    - **Settings** – The settings for scene (*scene.xml*), species (*species.xml*) and styles (*styles.xml*).
    - **Snapshots** – Layered snapshot visualizations for the end state of experiments.
    - *mte_data.dat* – The results output.
  - **sample** – Results of experiments with just 10 runs.
    - Same structure as **data** but contains saved experiments with their histories in **data/Completed**.
  - **failed** – Results of cancelled experiments showing inappropriate behaviour for higher social attraction range.
    - Same structure as **data**.
  - *mte_data.dat* – Main data file with experiment results.
  - *process.r* – R script used to process data.
- **tools** – The tools we used to conduct experiments and process their results.
  - *dotNetFx40_Full_x86_x64.exe* – .NET 4.0 Framework installer.
  - *muragatte_r72_bin.zip* – Muragatte binary files.
  - *muragatte_r72_bin-tp.zip* – Muragatte binary files with folder structure and settings files used in experiments.
  - *muragatte_r72_src.zip* – Muragatte source files.
  - *R-2.15.0-win.exe* – R installer.
- *vejmola_thesis_2013.pdf* – A pdf version of this thesis.