Nature Games: Collective Decision Making in Fish School

Master Thesis

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Abstract

In the era of emerging artificially intelligent systems, there is an ongoing struggle to achieve complex behaviours from nature. The behaviour of animal groups is one of the undergoing intense research in Swarm intelligence (SI), the study dedicated to the behaviour of artificial agents. From the flying swarm robots to an intelligent drone accomplishing a task by seeking a target, there is a continuous stream of research and development that is evolving our experiments from nature.

In this thesis, the collective-behaviour of fish is studied to see if the majority can achieve consensus in the multi-target environment. The experiment replicated in this thesis consists of a three-armed choice environment with fish divided into groups based on their trained target. The individuals are mixed to test if they can reach a general agreement by moving to the third target which has similarity to their trained target. The designed simulation model is based on the same experiment, where the group of fish have their rewarded arm as memory. The two distinctive fish groups are combined later for the testing phase to test if the mixed individuals of the swarm can reach a consensus. The Self-organised behaviour (SOB) of fish in the swarm is indeed a challenging task, considering how the real fish behaves with visual cues, spatial memory of rewards and precautions from predators. The scope of this work is limited to only one goal. How can a fish achieve consensus within a group? Is it based on the social information, personal information or both? A prediction based voter model is implemented to attain the fish behaviour mentioned above. The model has a majority rated rule approach; every agent decides the heading direction based on the multi-criteria (a) minimum distance to the known target and (b) cohesion on the decision taken by each agent in the communication radius. The direction which is voted by the majority is now the preferred heading direction of the local flock.

The results from the simulation are satisfactory, where more than 50% of the agents always achieve consensus in the mixed group experiment. Various parameters alter the behaviour of an agent in the swarm; the most important of them is the communication radius and the Field of view (FOV). Both parameters play a vital role in an agent decision-making, especially in the criteria (b) where cohesion is essential based on other agents opinion.

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Contents

1. Introduction

Technology is merely a reflection of theories and behaviours learned from nature over the course of time. In recent years, the study of animal groups collective-behaviour is one of the most inspiring natural sources of learning for computational science. The artificially designed agents are replicating the actions of such species, to understand the biological intelligence and evaluation of the decision-making process[38, 61]. The phenomenon of fish schooling has a long-lasting interest in ethology and ecology, widely spread across taxa and ecological contexts [5, 45, 57]. It has attracted much attention from statistical physics, computational sciences and theoretical biology as the case of SOB [21, 59, 62] and cognitive science. According to biology, a group of fish that stays together for social reason are called Shoaling, and if that unit of fish is swimming together in a direction in a coordinated manner, it is called Schooling [52]. This intelligent group behaviour of an organism is deeply studied in cognitive science and is modelled in computational science to bridge the gap between nature and artificial life. In the computer entertainment industry, the animal groups are also carefully studied and modelled to replicate their interesting collective behaviours. Today, the games industry is nearly creating the cutting edge graphics quality and details of nature. However, still, it lacks in the design of intelligent behaviour for agents. The focus of this thesis is to imitate the behaviour of a group of agents modelled in a simulation engine, to achieve consensus in a multi-target environment. The problem consists of multi-criteria where an agent needs to decides its best move based on minimum distance to the target but with maximum cohesion. In other words, it is a Multi-criteria decision-making (MCDM) problem for a Multi-agent system (MAS) in a multi-target environment. It sounds like a complex problem and it is more hard to achieve same behaviour in a computer simulation.

1.1 Motivation

The motivation behind this thesis is to understand and explore the swarming behaviour of fish school and how it can be simulated to seek a target given in a multi-target environment. The important questions to answer here are; What sort of information is more important in MCDM for an individual, personal or social information? How can a fish achieve consensus, if it is part of a mixed group where each individual has a different preference for the target? How the agent should make a collective decision within a group to reach a target mutually?

The primary objective of this thesis is to propose a new model of movement for agents in the swarm for solving this specific problem of consensus achievement in a multi-target environment.

Objective 1: Designing and modelling of a multi-target environment

A proposed movement model on every time-step to move in the multi-target environment. It applies force to the agent body to move in a specified direction, which is selected based on a controlled decision-making process. The decision is made based on personal or social information depending on an agent communication radius and neighbours.

Objective 2: Modelling a movement model for each individual in a swarm

The controlled decision-making process helps the movement model in the selection of best direction. On fixed time-step, an agent predicts a position from a directional angle notated as α within a specified radius around it and decides based on multi-criteria if the predicted point is the best direction to move. The criteria to select the best is the minimum distance to the targets and the maximum cohesion within the neighbourhood for that selected direction.

Objective 3: A controlled decision making algorithm to achieve consensus

While moving in a controlled algorithm, an agent can collide with various obstacles along the way. For example, walls in the environment and other agents who are physics bodies. The agent should not penetrate into these obstacles. A collision detection mechanism is designed to keep the continuous movement of individuals within the swarm.

Objective 4: Modelling a collision avoidance mechanism.

The above models are implemented in a simulation engine to test and analyse if the consensus can be achieved given the multi-criteria and a multi-target environment.

Objective 5: Implementation of the simulation model

A detailed evaluation of the results from the simulation model for possible test cases and parameters that might influence the behaviour.

Objective 6: Evaluation of simulation models results

At last, the understanding and comparison of our model result with the biological findings from the actual experiment.

Objective 7:Understanding and Comparison of our model with biological experiment

1.2 Biological Inspiration

Science and technology have long lasting relation with nature, without nature and its diversity, science would not have evolved this much. For everything to grow and prosper it needs a continuous source of inspiration.

> *"We still do not know one thousandth of one percent what nature has revealed to us."*
>
> —Albert Einstein[1]

We always learn and adapt things from the life, its behaviour and ever-changing climate. Science by its literal meaning is the collection of data organised in a form to deliver some knowledge about creations of the universe.

Behaviour; is the term that is used most widely in this thesis, how can we define it? In simple words, its the way of conduct of an individual. How one acts or reacts with another individual in an environment is referred to as its behaviour. We as human also have such various forms of actions, in our daily life and routine.

Likewise, animal's have their standard behaviour which is studied in the field of ethology. Why is behaviour so important? It is the way of interacting with others, responding to them or controlling the factors in the environment. In general, it can also be classified as the first line of defence for an animal in response to the changes in environment [36].

1.2.1 Animal Groups

The behaviour of animal groups which can also be referred as social behaviour is the major highlight of this thesis. In the Figure 1.1, the different types of animal groups with their respective behaviour category is shown.

There are various reasons why an animal adopts a social behaviour. It can be for the search of food, hunting, mating, migration to another place, or survival. Animals who undertake such social behaviour are characterised as flocking, herding, shoaling and schooling based on their type respectively [17, 37, 41, 56]. The social behaviour also results in the creation of different behavioural patterns. In ethology, these patterns are intensely studied to understand the evolution of animals over time. Since there are millions of various animal species and each one of them behaves differently from each other. There is a set of typical behaviour and patterns exhibited from species. Most commonly, all species need to eat, reproduce, be safe from a predator (not to be eaten) [4].

[1]Wikiquotes Albert Einstein (1879 - 1955)

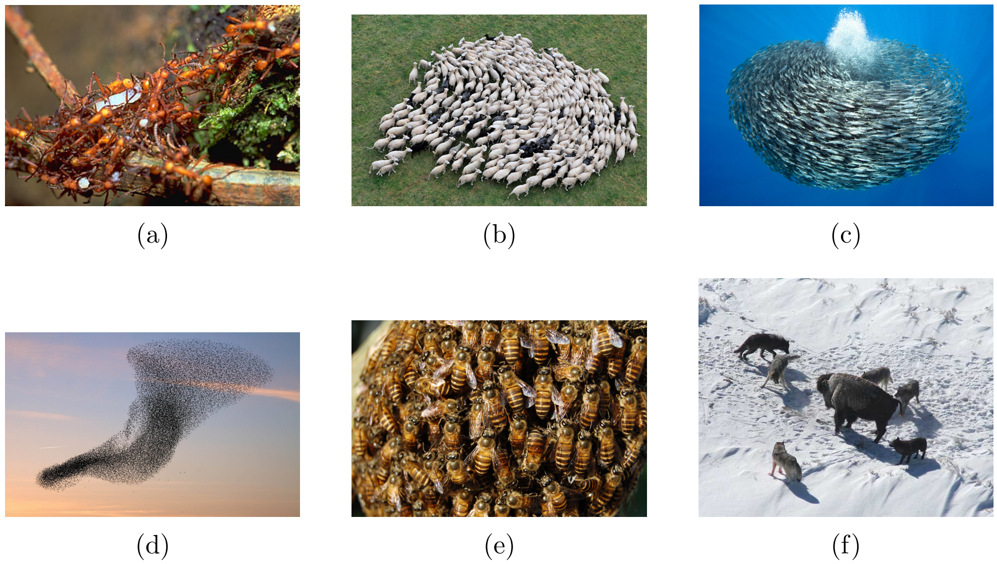


Figure 1.1: Different type of animal groups in social behaviour (a) Ants Flock [1](b) Sheep Herd [2](c) Fish School [3](d) Birds Flock[4](e) Bees Flock [5](f) Wolf Pack [6]

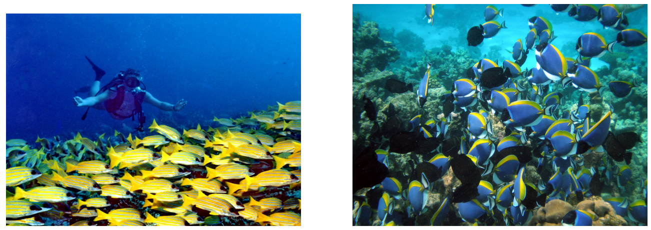
They adopt following types of behaviours [3].

1. Reproductive - the mating behaviour of the animal to attract opposite gender.
2. Foraging - finding what to eat to gain more energy.
3. Defensive - anti-predator behaviour, staying safe and not to be eaten.
4. Communication - interacting with others through sight, sound or chemicals.
5. Territorial - maintaining a private space.
6. Dispersal - moving away from the birthplace.
7. Social - moving in large groups of the same type.

1.2.2 Fish Schooling

Fish schooling is one of the most beautiful natural behaviours in animal groups, which still needs to be explored and modelled. The group of fish which stays together for social reasons or migrate together to another destination are known as Shoaling or Schooling respectively. The terms are used interchangeably, but they refer to the behaviour of fish in large numbers [44].

[1]https://www.britannica.com/animal/ant/images-videos
[2]https://www.boredpanda.com/sheep-flock-herd-photos/
[3]http://allthatsinteresting.com/schooling-fish
[4]https://www.howitworksdaily.com/why-do-birds-flock-together/
[5]http://www.naturalbeekeepingtasmania.com.au
[6]https://en.wikipedia.org/wiki/Society



(a) (b)

Figure 1.2: Fish School of two different type of specie. (a) Fish Schooling in specified heading direction [1](b) Fish Shoaling in random heading direction but still staying closer [2]

1.2.3 Self-Organised Behaviour

It is defined as a complex behaviour of individuals in large-scale distributed systems. It can also be referred as emergence behaviour or self-organised behaviour of agents based on their local information and interactions. The process is very spontaneous and is not controlled by any external agent. The term organisation is widely used in computational science for MAS and how they behave to organise themselves. Such behaviour is dynamic and emerges from the local interaction of agents within a small neighbouring radius over the course of time and finally reaches to a global stable state [50].

Animal groups in social behaviour are self-organised, and they only share information to their local neighbourhood. Likewise, a fish in the group has a defined area of communication, and hence it stays together with other agents in the local region to reach a stable global state. These local changes and interaction between fish emerges as a universal behaviour of fish schooling, which seems very complicated on global scale. However, it is based on straightforward ground rules of movement within swarm [57].

1.2.4 Collective Decision Making

While moving in large groups, it is most likely that an agent gets influenced by its neighbours and social members. Every individual has two sets of information to process while making a decision, personal and social information. The personal information is what comes from an agent training or memory (some past incidents or events). Social information is gathered from other individuals within the group.

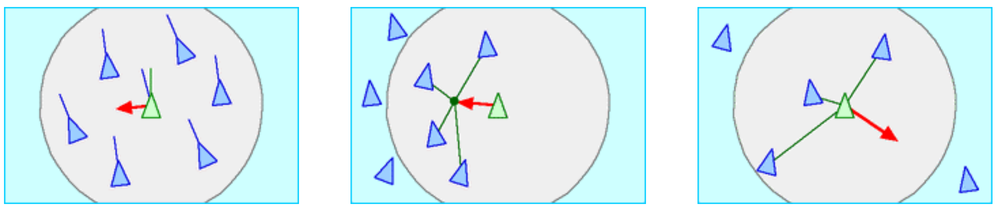
The *best-of-n* is a Multi-objective problem (MOP), that needs to be solved by decision makers, which are influenced by social information within a group[61]. Collective decision-making (CDM) also referred as Consensus Decision Making often leads to choices which are very different from the individual personal preference. However, being a member of the group, the majority favourable votes on the alternatives change the course of decision for the whole group.

[1]https://www.britannica.com/animal/ant/images-videos
[2]https://www.boredpanda.com/sheep-flock-herd-photos/

1.3 Swarm Intelligence

If we want to replicate the nature, we first have to understand how it works and how behaviours emerge in animal groups. The field of study, which deals with the computational model of such swarm behaviours is called SI.

In 1987, the very first SOB model of a bird was created by C.Reynolds, which is labelled as BOIDS [45]. It is an artificial life simulation model for flocking behaviour of birds in a distributed environment. The BOIDS agent has three basic rules to follow in their local space to achieve a complex behaviour, shown in Figure 1.3.



(a) (b) (c)

Figure 1.3: BOIDS Flocking Model (a) *Alignment* (b) *Cohesion* (c) *Separation* [45]

BOIDS Movement model with three major steps[1]:

1. **Alignment** - move towards the average heading direction
2. **Cohesion** - move towards the average position of flock (centre of mass)
3. **Separation** - collision avoidance with other agents

1.4 Bridging the Gap

To summarise the motive and scope of this thesis. We would combine the significant aspects discussed in this chapter such as nature, self-organised behaviour, collective decision making and fish schooling. In this thesis, a simulation model is designed and implemented to replicate a biological experiment. In 2013, Miller's et al. experimented on a total of 256 real golden-shiner fish in a multi-target environment with a set of predefined targets[38]. In training phase, the fish were divided into 16 groups each containing 16 fish. Each group was further divided into two sets and trained on different targets in exchange for a reward of food. After the training phase is finished, in the experiment phase, the fish from both groups were mixed to see if they can achieve consensus on the third target, which contains visual cues of both trained targets. We will refer to this experiment as Miller's Experiment (MiE) throughout the document.

The fundamentals of our simulation model are based on MiE, but with few refinements and modifications in the training phase since it is simulation model and the experiment

[1] https://www.red3d.com/cwr/boids/

phase is more crucial part to test, if consensus can be achieved. Also, in our model instead of visual cues information, the preferred target position is stored in the memory of an agent. This information is used in the decision-making process of the simulation which is based on prediction based approach inspired by work of Valentini et al. [62]. They used the voting model to rate the sites given in an environment. Each agent evaluates the sites rating and prefers the one over the course of time. In our simulation model, we use the voting model to rate every direction to take at every time-step. Every agent on a personal level rate the direction to take and the information is shared with the neighbours to find out the best direction for all in the local flock.

1.5 Structural Overview

Nature is a popular topic, and it is challenging to cover all aspects of natural behaviours and computational science together in one piece of work. That is why to understand the important behaviour of animal groups and their relation to the computational science model discussed in this thesis. A brief description of every connected branch is highlighted in following chapters.

- **Background** - An overview of nature, animal groups behaviour and computational science inspiration is highlighted. The dive into the origin of Intelligent behaviours and the first model of an autonomous agent is over-viewed with fundamental aspects relevant to this thesis. The structure and major components of an autonomous agent. Overview of biological experiment which is replicated in simulation model. What is Consensus and which type falls into the scope of this thesis?

- **Literature Review** - SOB is an exciting topic, and much research has already been done in the past to understand and replicate such complex behaviour of nature. This chapter gives the scientific proof and work of others on the related topic. A brief overview what communication topologies are used for selecting neighbours.

- **Methodology** - This chapter explains the proposed model and its elements in detail. The design of the simulated environment, the essential parameters involved in the simulation, the agent model design and the decision-making model which controls the overall process of an agent movement.

- **Simulation Model** - This chapter is highly related to Methodology, and it shows the algorithms, simulation model working and step followed to achieve the final results.

- **Evaluation** - This chapter discusses in detail the results of the simulation model, different test cases and best combination of parameters to achieve high consensus.

- **Conclusion** - How the proposed model results are compared to the biological experiment of MiE, What can be improved in the model itself and the future of the work?

2. Background

Nature has its own of way inspiring us, and it has always been a great source of inspiration for computational science and natural computing. For anything to exists, there needs to be some source of existing element that can transform into another representation. In Artificial intelligence (AI), that source of data is from nature and its fascinating behaviours and biological patterns. Numerous algorithms are developed to solve the complex real-world problem through Nature inspired intelligent (NII) techniques[63]. There is still on-going research in the field to understand biological patterns and phenomena in nature. The most important factor in the natural phenomena is of the information processing and how it is done in social groups in a very optimal, self-organised and distributed way [2, 53].

There are many scenarios where social group collective decision making takes place to solve various problems. From daily life conflicts to the industrial problems, i.e. supply chain management, renewable energy, business management [32, 33, 39, 65] we do face multi-criteria problems time to time. It has been a much-researched area in the science to find an optimal solution to the MCDM [13, 25, 64]. The MCDM problems can occur in different situations e-g, a man wants to buy a car, the least two criteria are the cost and comfort. A simple 2D matrix of conflicting criteria, where the cost should be minimum as possible, but comfort should be maximum on the other hand. Let's suppose there are more criteria to consider in buying car and decision has to be done in a small family group. Here is where all decision makers need to have a collective agreement on specific criteria for best decision [8]. There are different ways in which MCDM in social groups are solved; and there has been much research done on the development of these approaches [58, 66].

2.1 Multi-Agent System

Multi-agent systems are the distributed artificial systems that consist of several agents which are given a task to achieve. What is an agent?

2.1.1 Agent

An agent is an artificially intelligent autonomous entity which takes input from the environment through sensors, does some processing on that input, act upon it through actuators until a goal has been achieved [47]. Some key elements of an agent are situatedness, autonomous, flexible (responsive, pro-active, social) [28, 67]. Where *situatedness* refers to an agent that takes input from the environment through sensors and perform actions on the environment. *Autonomous* means when an agent can take control of its actions and internal states without any external input from human or other agents. The *Flexible* agents are *responsive* to environment in a timely manner. They are *pro-active* who could take the initiative where needed with goal-directed behaviour and finally a flexible agent should be *social* who could interact with other agents to exchange information [28, 67].

Intelligent agents are classified into different categories [47], but in the context of this thesis, we will look at the goal based agent which has a target to achieve and its interaction with the environment. In figure Figure 2.1, an agent model is shown at the abstract level. The agent model communicates with the environment through sensors and process that information to take further actions until a goal has reached.

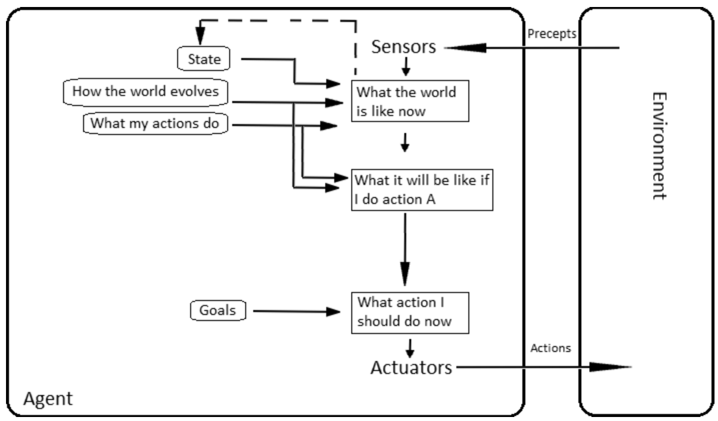


Figure 2.1: An intelligent agent model and goal based approach [47]

An agent in a MAS has a target (goal) to achieve in a distributed manner, where there is no centralised system to control the behaviour of agents. In fact, all the agents act on their own, such type of behaviour is called SOB.

2.1.2 Self-Organised Behaviour

It is a complex behaviour of individuals in large-scale distributed systems. It can also be referred as emergence behaviour of agents based on their local information and interactions. The process is very spontaneous and is not controlled by any external agent or central system. The term organisation is widely used in computational science for MAS and how they behave to organise themselves. Such behaviour is dynamic and emerges from the local interaction of agents within a small neighbouring radius over the course of time and finally reaches to a global stable state [50].

2.1.2.1 Properties

There are some key properties which are necessary for an agent to be self-organized in a MAS [50];

1. **Decentralized control** - this property is essential for a self-organizing system to work, the interactions are limited to local information.

2. **No external control** - the system should be autonomous and only internal decisions are to be made.

3. **Dynamic** - the system should evolve with time and it is continuous.

2.1.2.2 Characteristics

Some important characteristics of self-organizing systems [50];

1. **Global state** - the system reaches a global state, which is also related to emergence phenomena.

2. **Emergence** - only with local interactions a global state is achieved hence no central control.

3. **Local rules** - every individual has simple local rules to follow. The personal information of every individual is processed locally hence doesn't define any global pattern.

4. **Dissipation** - the system has to stabilise at some state; otherwise it will keep on changing continuously.

5. **Instability** - any change in parameters of individual behaviour will result in a global change in the pattern of the system.

6. **Multiple equilibria** - is observed when many possible attractors for stable states are present in the system.

7. **Criticality** - the presence of threshold effects or phase change in the system.

8. **Redundancy** - insensitivity to damage cause of replication of components in the system.

9. **Self-maintenance** - the system should be able to reproduce or repair itself and behaviour when needed.

10. **Adaptivity** - in the dynamic change in environment; the system should be able to reorganise the behaviour.

11. **Complexity** - the system gets complex with the combination of different local behaviours which results in a complex global pattern.

12. **Hierarchies** - are part of multiple nested self-organized system

In MAS, the modelling of the complex behaviour is primarily from the animal groups behaviour, where only with the exchange of local information, a very complex behaviour is achieved globally. Those complex behaviours are seen in a variety of animal groups from birds and bees flocking to schooling of fish and insects swarm. The study of these complex behaviour of animals group comes under the field of SI [10, 11], in which researchers have recognised and formed algorithms which depict the natural behaviour of animal groups to solve complex problems. The most famous algorithms of SI are Ant Colony Optimisation [9] and Particle Swarm Optimisation [29].

In the context of this thesis, we will only talk about how in animal groups the collective decision is formulated if the group has to seek any target in the multi-target environment. The decision-making problems consist of different option in a set, and one of that option is selected as the best. In large animal groups, the decision making takes place in scenarios, where there are multiple and often conflicting criteria to be considered at the same time. When a large group of animals decide collectively on similar criteria, a complex group behaviour evolves on global scale [21]. Every individual in a group determines based on its personal information which alternative best fall into the criteria. The selected best alternative is then shared with others in the social group and based on social information the decision making of an individual is influenced[38].

2.2 Multi-criteria decision-making

In multi-criteria decision making, there are criteria which are conflicting with each other, and the alternative should be selected at the same time based on these criteria by all individuals of the group. In such scenarios, a consensus among all individuals has to be reached.

The key elements of the MCDM are;

1. The criteria on which the decision should be made.
2. The alternatives to be analysed for the Criteria.
3. A personal best alternative selected by an individual.
4. A global best alternative selected by all decision makers.

There are different approaches to solve MCDM problem and they can be classified into three major categories [26, 33, 66];

1. **Ranking-based approach** - This focuses on giving numerical scores to each alternative to evaluate its performance and the criteria overall performance in the decision-making process.
2. **Majority-based approach** - This focuses on voting process model in which the decision is based on the opinion of the majority of individuals in the group of decision makers.
3. **Consensus-based approach** - This focuses on reaching a certain level of agreement within decision makers until the decision made is accepted.

There are various methods to achieve MCDM, and each method uses a numeric technique to analyse and choose the best alternative from a set of discrete alternatives. The Weighted sum model (WSM) is one of the earliest and most widely used methods to solve the MCDM problem by assigning weights to the alternatives. It is beneficial, especially in the single dimension problems. Likewise, Weighted product model (WPM) is a considered as a modification of WSM, which has been proposed to overcome weaknesses of WSM. In 1980, an Analytical Hierarchy Process (AHP) method was proposed by Saaty, and later different modifications of it came out to overcome the weaknesses of previous method [48, 58].

Any decision making technique that involves numerical analysis of alternatives have following important steps to consider;

1. The relevant criteria and alternatives to be determined.
2. Numerical measures assignment for all criteria and alternative.
3. The rank of each alternative from given numeric measures.

Let's take a look at how the criteria and alternative is represented in WSM for a MCDM problem. Given there is a set of n decision criteria denoted as C_1, C_2, C_3,..., C_n and a set of m alternatives which are denoted by A_1, A_2, A_3,..., A_m. The performance value associated with each alternative in terms of each criterion is represented as a_{ij} along with weights for each criteria represented as w_j. The best alternative can be determined from the given expression in case of maximum criteria;

$$A^*_{WSM-score} = \max_i \sum_{j=1}^{n} a_{ij} w_j, \quad \texttt{for i= 1,2,3,...,m} \tag{2.1}$$

where $A^*_{WSM-score}$ is the score calculated for the best alternative [58].

2.3 Consensus

A consensus in simple terms is defined as a general agreement within a group of people, where every decision maker has its own view but an overall agreement is reached at the end to solve the problem. In MAS, through collective decision-making large complex problems are solved. The consensus can be classified into two types of achievement problems as stated by Valentini et.al in their work of best of-n problem [61] and originally the taxonomy of collective decision-making presented by [12] as shown in figure Figure 2.2;

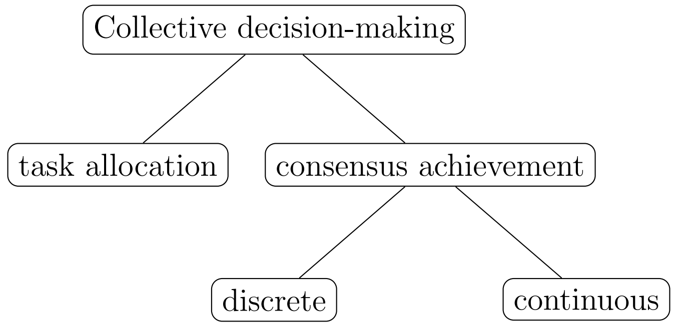


Figure 2.2: Taxonomy of collective decision-making processes [12] [61]

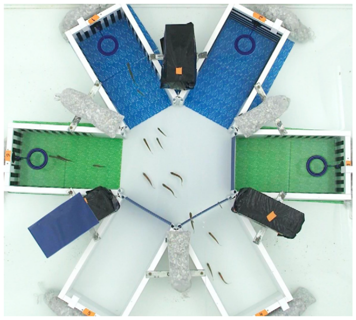
1. **Discrete** - This type has a finite set of choices and is countable. There has been sufficient research done on the approaches of how to achieve discrete consensus in a problem with finite options such as RoboCup competition from 1997 [30] to the swarm robotics in site selection recently in 2017 [60–62].

2. **Continuous** - The type has infinite choices and is measurable. This type of consensus is achieved in problems where there is continuous motion going on such as *flocking*; where the swarm of agents are heading to the same direction in two or three-dimensional space [45] [14, 51].

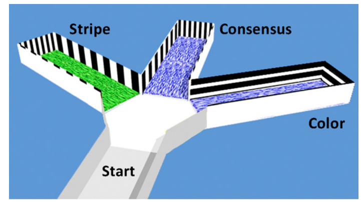
2.4 Experiment Overview

2.4.1 MiE Approach

In this thesis, a biological experiment which we are referring to as MiE is replicated in the computer simulation. We will briefly discuss here the overview of experiment and its major highlights. In the MiE, a group of golden shiner fish were trained on predefined targets, in reward for food. After several training trials, the group of fish were divided into two separate groups based on their known targets (A and B). The targets are defining a rewarded arm in the radial set of environment. In the Figure 2.3(a), the fish tank with six radial maze arms are shown. In one experiment trial, only three of the given arms were used for exploration and one of the Start Arm, where group of fish were put together as there starting position. In the two sets, the one on the left is always the Stripe Arm for the training of agents Group type A, and the one on the right is the Colour Arm for Group type B. The middle one is the Consensus Arm which contains the visual information of both Stripe and Colour Arm [38]. The trained agents are tested with two major experiments (a) Mixed group - where A and B type agents are put together for testing (b) Unmixed group - where either A or B type agents are put into the maze Start Arm.



(a)



(b)

Figure 2.3: MiE on golden shiner fish; on left a six arms environment with two similar textures arms and on the right the three arm environment with unique arm textures and one starting arm [38]

The 2.3(b), shows the test environment where the three-arm paradigm is used for testing fish in the mixed group. The experiment results shows how many fish from group have achieved Consensus. The decision made was either based on their personal preference or their social interaction while travelling in the maze. In this thesis, we want to replicate the same experimental environment in the form of computer simulation and test if our self-organised agents can achieve consensus too if put into the similar environment setup. We have used the same environment design as the MiE, but with only three-armed choice as shown in 2.3(b).

The biggest challenge in replicating a biological experiment is to consider all the parameters that could affect the flow of simulation and agents decision. First of all, we divided the experiment into small parts to figure out what is the problem in hand and how it can be tackled? It is clear from the environment in 2.3(b), that is a multi-target environment for a MAS. Secondly, there are a discrete set of targets which needs to be defined as the trained memory to the simulated agents. Finally, what are the criteria for the decision making in a swarm of fish with the multi-target environment?

2.4.2 Weighted Voter Model

During our research for self-organised behaviour and collective decision making in groups. We went through several problems and solution of how the MCDM is handled in different real-world problems which are from different fields such as supply-chain management, business intelligence, fuzzy systems, economics and multi-agent systems. The most relevant to our problem is, of course, the problems of multi-agent systems and collective decision making in swarm robotics or simulations.

The work by G. Valentini et al. is closely related to our problem, they have used the Weighted-voter model (WVM), in their work on self-organised collective decision making to achieve consensus within group of robots. Their approach of solving *best-of-n* decision problem consisted of a controlled algorithm, which chooses the best site out of N alternatives. Every site had a quality parameter associated with it, which every agent will evaluate on a visit. Over the course of time, agents will reach consensus on the preferred site [60–62].

Their work on robots in a multi-site environment is very closely related to the approach of MiE. Instead, of robots MiE has fish which are trained over a discrete set of targets in a static environment before tested for the decision making. Hence, it narrows down our scope to look for how to achieve continuous consensus in a finite set of criteria with the multi-target environment.

In the next chapter, we will discuss how our work is related to the previous work that has been done in the collective decision making of the swarm and fish schooling.

3. Literature Review

In the previous part, we had an overview of all subtopics that are relevant to this thesis. In this chapter, we will highlight the related work on the topic of fish schooling and collective decision-making.

Fish schooling has been a much-researched area for biology and natural computing [14] [21, 38]. The complex behaviour of animal groups is associated with a concept of 'collective minds' [16], where every individual in group process the shared information to decide where to move in the environment. The individual's decision making is based on the factors of environment and their surrounding individuals. The information is perceived through visual cues within a specific range of an individual viewing range and also the motion of the others [19, 54]. The Figure 3.1 shows the viewing range of two fish of fresh water family, where the tail of a fish is the blind spot. The study of Pita et al. presented a quantitative prediction for social interactions of zebra and golden shiner fish by using their visual system to sense the position, orientation and spacing within group[43]. The effect of visual sensing allows more accurate decision making and information processing in a small group around an individual[54].

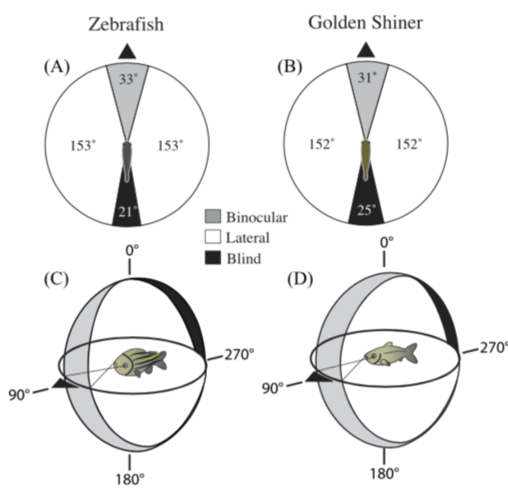


Figure 3.1: Visual field configuration in the 2D horizontal plane from the top view in (A) zebrafish and (B) golden shiner. The 3D depiction of (C) zebrafish (D) golden shiner respectively [43]

The collective behaviour of animal groups has considerably been studied more in the form of mathematical modelling, starting with the first agent-based model BOIDS by

Reynolds in 1987 [45], that depicts the movement of birds flocking in a same heading direction forming a complex behaviour. This agent-based model also depicts the movement of fish schooling. Later, in the model different steering behaviours of the flock has been modelled such as seeking, leader-follower, flee, arrival [46]. Since then the collective behaviour of animal groups has been studied in much more detail from optimisation of the particles in the swarm to the problem-solving in MAS [9, 11, 29] and in the swarm robotics [12, 30].

The group size in the collective decision-making plays an important role, the information shared within the group is deciding the course of the heading direction of the swarm. If the individuals in the group have a different source of information, then the conflicting information can still result in an average heading direction, and hence increase the efficiency of collective decision-making [15, 55]. The different character of individuals can also emerge during the movement of the swarm, even though there is no pre-condition to state that the individuals have to act like a Leader, but some inform individuals take charge and lead others to the direction they are heading. The few informed individuals can lead to a consensus decision in case of the conflicting source of information, where individuals decide to move in a travel direction preferred by majority[15, 19, 55]. Such, leadership characteristic and information sharing are seen in the group of honey bees where few informed individuals who have information about the food, inform other individuals by doing a waggle-dance. This way they recruit new individuals to be the informed members and hence the migration to the new place takes place [23, 24, 49].

The modelling of the fish school behaviour has given researchers a better understanding of the collective motion of fish with different environmental and parameter settings. The agent-based modelling of fish school [45], did open new dimensions for the researcher to replicate the behaviour of fish, by modelling individual rules, biological patterns and network topology of an individual to do communication with the neighbours[5] [27, 40, 42]. The insight of the existing primary fish school models are analysed jointly with the biological aspect of fish school behaviour [34]. The study concludes the significant components which should be part of a fish school modelling; (a) the motion of a single fish (b) interaction among fish (c) the nature of stimuli used by an individual fish (d) network topologies to select neighbours (e) discrete number of neighbours based on visual processing (f) physiological and behavioural changes [34].

The first model of fish school is based on an individual level which follows three basic rules of BOIDs model [45], alignment(orientation), cohesion(attraction) and separation(replusion). Where alignment is the heading direction of the group, the cohesion is the how close they are towards the centre of their group, and the separation is the avoid distance from each other [17, 40]. The Figure 3.2 shows different zones around a fish in a three-dimensional space [22] with a blind spot at the tail side of fish in the shape of a cone.

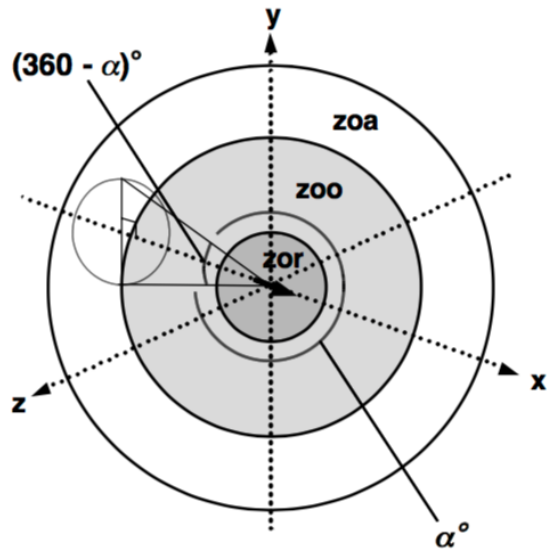


Figure 3.2: The zones are representing; zone of orientation *zoo*, zone of attraction *zoa* and zone of repulsion *zor*, around an individual in three-dimensional space[22].

The other models of fish school as discussed in [34] is synchronous/asynchronous self-propelled particles models [1], the social force models, physics of collective motion and self-organisation. Even though there has been a decade of research done on the implementation of such behaviour models of fish school, still there is more aspect to explore and study with relevance to the biological experimented data and analysis [31, 34]. The social cognition within the group of animals plays the crucial role in the formation of patterns and group complex behaviours. The selection of the neighbours by an individual depends on the modelling of the network topology. The two common communication topology which are used in individual based-models [18, 20] are (a) a zone-based model Figure 3.2 (b) a Delaunay based-model [6].

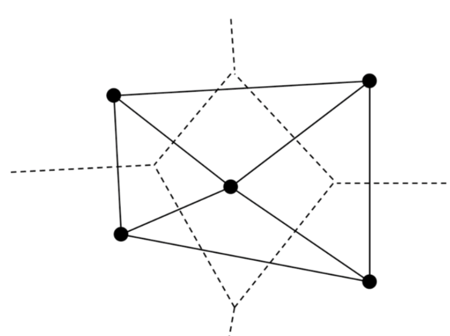


Figure 3.3: Delaunay Triangulation of an individual communication topology using Vornoi partition where black solid circle shows the individuals and solid lines show the Delaunay edges[31].

In the zone-based topology, all the individuals that are inside the zone area are considered as communicating individuals whether it is the attraction (zoa), replusion (zor) or orientation (zoo). Whereas, in Delaunay based-model, the communication is based on Delaunay Triangulation (Voronoi partition). The two individuals, if present inside the boundary of Voronoi cells are considered to be neighbours [6]. The Delaunay triangulation is obtained by connecting all individuals by the Delaunay edge. The Figure 3.3 shows the neighbourhood topology of a Delaunay based-model[31]. Both communication topologies have their setbacks depending on the density of swarm and weights of orientation and attraction, the behaviour of the two models affects the emergence of swarm[31]. The communication between agents is the most important element of a swarm behaviour, it highly affects the results of agent decision-making process.

In the next chapter, we present our proposed model which is based on a biological experiment called as MiE; we use the zone-based model topology for communication of an individual-based agent with opinion-based approach for collective decision-making in multi-criteria problem.

4. Methodology

In this chapter, the proposed model is discussed in detail, which is designed to achieve consensus in a group of fish school. As previously discussed, the objective of this thesis is to replicate MiE to understand the natural behaviour of a group of fish [38] in a multi-target environment. The model is designed reasonably, taking into consideration a generic agent model and a multi-target arena design.

4.1 Environment

There are two different environment design for the model, which are referred as following in this thesis context.

1. **Environment 1** - Three-armed choice based on MiE environment.
2. **Environment 2** - A square-shaped boundary environment.

4.1.1 Design

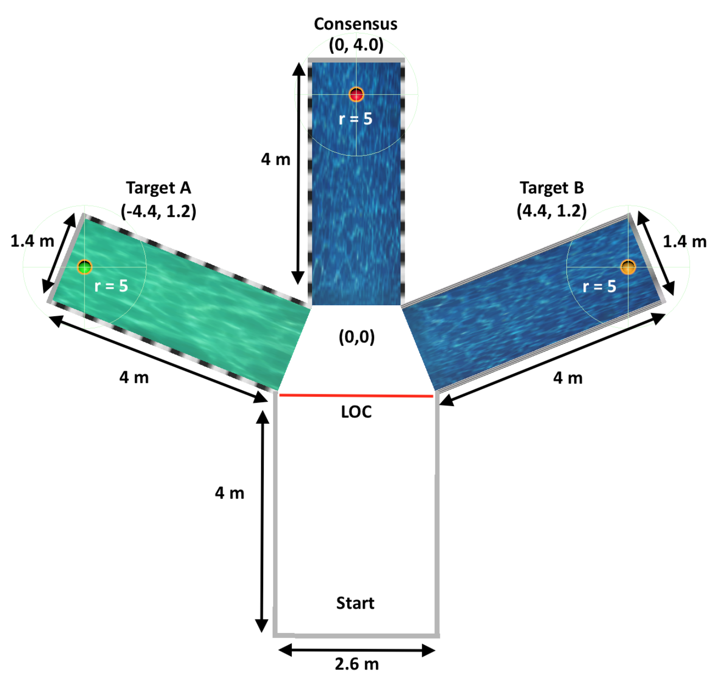


Figure 4.1: Environment 1: A three-armed environment based on MiE. The Start Arm in white colour is the initial place for spawning of fish; the middle arm is Consensus, Left is the Target A and Right is the Target B.

In Figure 4.1, the design of Environment 1 is shown, which is based on the MiE approach used in the actual biological experiment. The environment only contains one set of a static environment with three fixed arms [38]. The arm at the bottom with white base colour is the Start Arm with 2.6 x 4 m area, this is initial area where fish agents are spawned in Idle state. The above three-arms are the target arms. Each target arm has an area of 1.4 x 4 m area. The middle area is the free zone which is connecting all the arms. The agents spawn in the start arm passes through a control point which is shown as a red line at the end of start arm.

The label of the Targets is A, B and Consensus which are placed at the end of the arm. These labels will be used throughout the next text. The targets are shown as a sphere in different colours, such as green sphere is Target A, yellow in B, and red is the Consensus. The convention used in the MiE for the arm was Stripe Arm (Target A) and Colour Arm (Target B). In this thesis proposed model, they are only referred as the Target A and B respectively. The position of these targets is stored as in agent's brain.

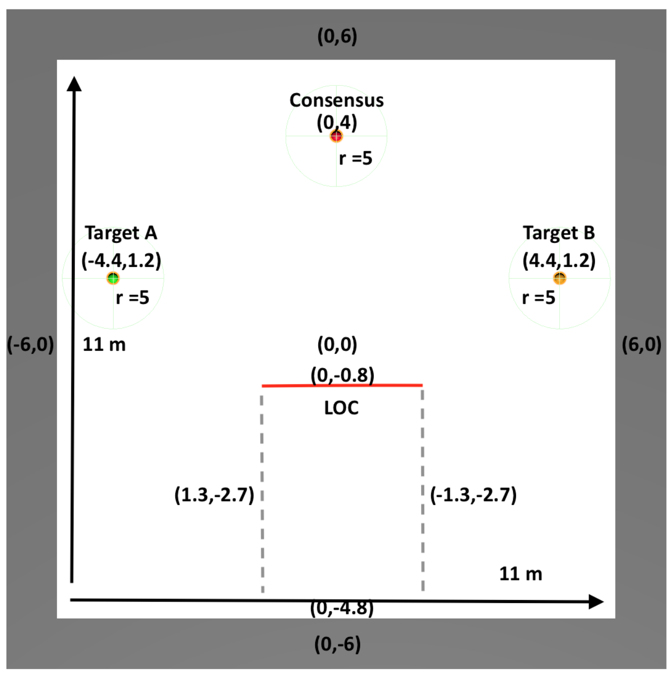


Figure 4.2: Environment 2: A squared shape environment with boundary in grey colour.The targets are defined at same position as in the Environment 1.

In Figure 4.2, the design of Environment 2 is shown which is a squared boundary environment with targets defined at the same coordinates. The total area of this environment is 11 x 11 m. The agents are spawned in the region below the origin (0,0) which is represented by dotted grey lines it is same as the Start Arm in Environment 1, but with no walls to collide. The label and the colour coding of targets are same as Environment 1. The red line represents the Line of control (LOC).

4.1.2 Target

Each target which is an object (sphere) placed in the 3D environment has certain radius r which helps in detecting if any agent has entered this target region. In the model, the agents are not designed to have the visual cues due to technical limitations. Instead, the position of the targets is stored in the memory of agent when they are in the arena.

The targets are set to the fixed position in the environment, which means they are static throughout the simulation period. Each target has its collision mechanism to check if an agent has reached its region. The light green circle around each target shows the radius r when an agent reaches inside this radius, the agent is set to the state of *Arrive* and has a character as *Achiever*. These states are discussed in detail in next section of Agent.

The MiE initially contains the training modules to develop a memory of fish for a rewarded arm. In our model, the training module is skipped instead built-in information of the rewarded arm is stored in the agent's brain.

4.1.3 Line of Control

To make sure, all agents start seeking their target from the same point in the arena. A thin LOC is added near to the origin (0,0) in the environment. This control point is a bounding box, which enables the seeking behaviour of an agent when they cross it. Hence, it ensures that the decision-making process of an agent starts only after this control line.

4.2 Autonomous Agent

In our model, the agent is a fish which has to be a self-organised entity to be able to make the decision independently based on its local information. The decision of an agent is influenced by its neighbours and the environment setup.

Following are the key components of our agent model:

1. Agent Brain
2. Communication Radius
3. Agent State
4. Agent Character
5. Predicted Position
6. Collision Avoidance

4.2.1 Agent Brain

Every autonomous agent must have a brain, which is like a memory block that contains all information related to tasks within an environment e-g what to, where to and how to? In our agent model, the essential information for an agent is the target position in the arena. The training model of agents does not include as part of this simulation, and hence, we directly wanted to test if the experiment model is successful in achieving consensus with pre-defined information. The MiE had visual information of target arm trained into the fish brain over time, that is why for a real fish the information of middle arm consensus was identifiable. Because the consensus arm contains the visual information of both trained targets. The image processing and integration of spatial memory into simulated agents get complex, which is why we chose to follow a simple approach of having a two-dimensional vector in $\mathbb{R}^2$ which represents the position of a target stored in the agent's brain. Each agent has information of two targets with equal weights, one of the target is the trained target and other is the consensus target which has half visual information like the trained target.

1. **Group type A:** Target A and Consensus world position in the arena.

2. **Group type B:** Target B and Consensus world position in the arena.

4.2.2 Communication Radius

Every agent has a local communication radius which acts as a radar for it to track how many other individuals are near to its position to exchange information. Based on the zone-based model for communication topology, the zone for selecting the neighbourhood is referred here as C_r of an autonomous agent. The repulsion is from the zone of avoidance, which represents the radius of bounding box around agent model to avoid penetrating into any other object in simulation.

4.2.2.1 Field of View

In Figure 4.3, the FOV is shown in two different ranges Narrow and Wide. The Narrow view represents a range of 180 degrees and the Wide represents the range of 270 degrees. This viewing range helps filtering the individuals who are within the communication radius, not every individual is considered as a neighbour. Only individuals who falls in the range of defined angles are added to the neighbouring list. Hence, the information is exchanged between those selected individuals.

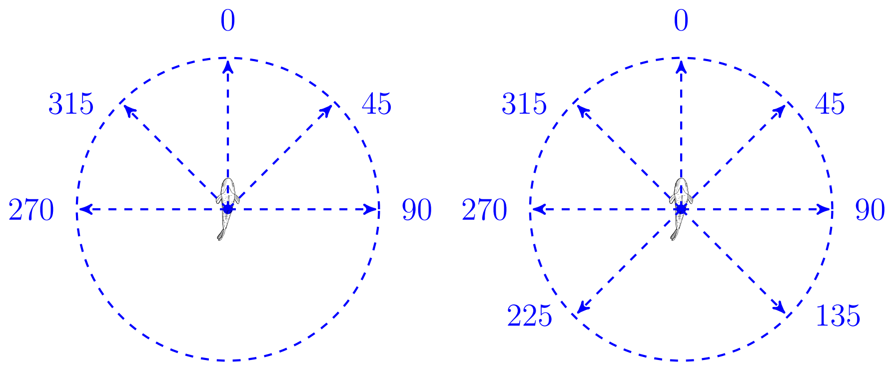


Figure 4.3: An agent with defined FOV in blue dashed lines (left) Narrow range and (right) Wide range of angles. The difference between angles is fixed to 45 degrees

4.2.2.2 Neighbourhood

Once the individuals are in the communication radius, they are further refined based on the visibility of agent's viewing range as explained above in FOV. The view of a simulated agent is created based on the real fish view, where the tail side of fish is a blind spot. If an individual is within the communication radius but is positioned on the tail side. It cannot be considered as a selected individual for the neighbourhood.

To refine the list of neighbours and check if they are visually visible to an agent, the dot product is calculated between the individual agent i and other agents based on their local position.

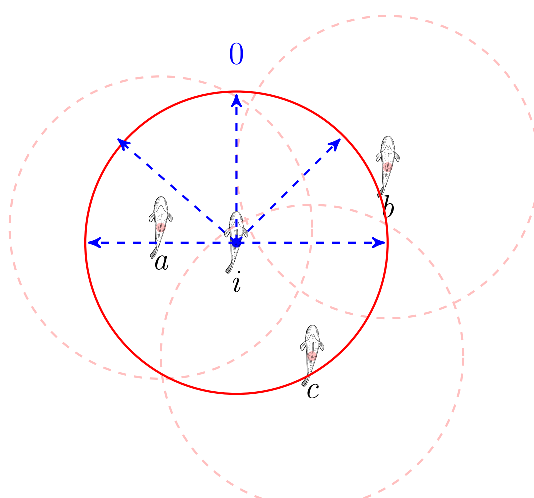


Figure 4.4: Refining neighbours from C_r and FOV directional angles. An example of an agent i three other agents.

InFigure 4.4, the selection of neighbours is shown for the individual agent i, which is positioned in the centre with solid red circle C_r and dotted blue lines to show FOV.

The zero angle shows the heading direction of an agent in local-space. In this scenario, the agent c would not be added into the neighbour list as it is on the tail side of fish and also out of FOV. The agent b is also not considered as it is out of communication radius. Only the agent a is added into neighbour list as it falls into the viewing angle and communication radius.

4.2.3 Agent State

In Figure 4.5, the states of an autonomous agent are shown. The states are set using a controlled algorithm throughout the model. Initially, when all agents are created in the Start Arm, they are in *Idle* state, once the movement starts they go into *Wander* state which lasts until an agent crosses a LOC. This state led them to walk straight in the Start Arm to reach the borderline.

A LOC is a small doorway to the multi-target environment which is to make sure that all agents go to *Predict* state only when they reach a specific position in the arena. In the *Predict* state, each agent looks for a *pBest* direction within its local-space. This *pBest* direction is calculated based on an angle α defined in a certain FOV of agent and based on majority opinions on a α, the one with the majority rating is selected as *gBest* for movement of the flock.

At this stage, every individual within neighbourhood goes to *Seek* state and the position is reached. If the reached position is not any of the target position, the agent goes back to *Predict* state again until it finds any target. Once, a target has been reached an agent goes to the *Arrive* state, and start rotating around the target as celebration.

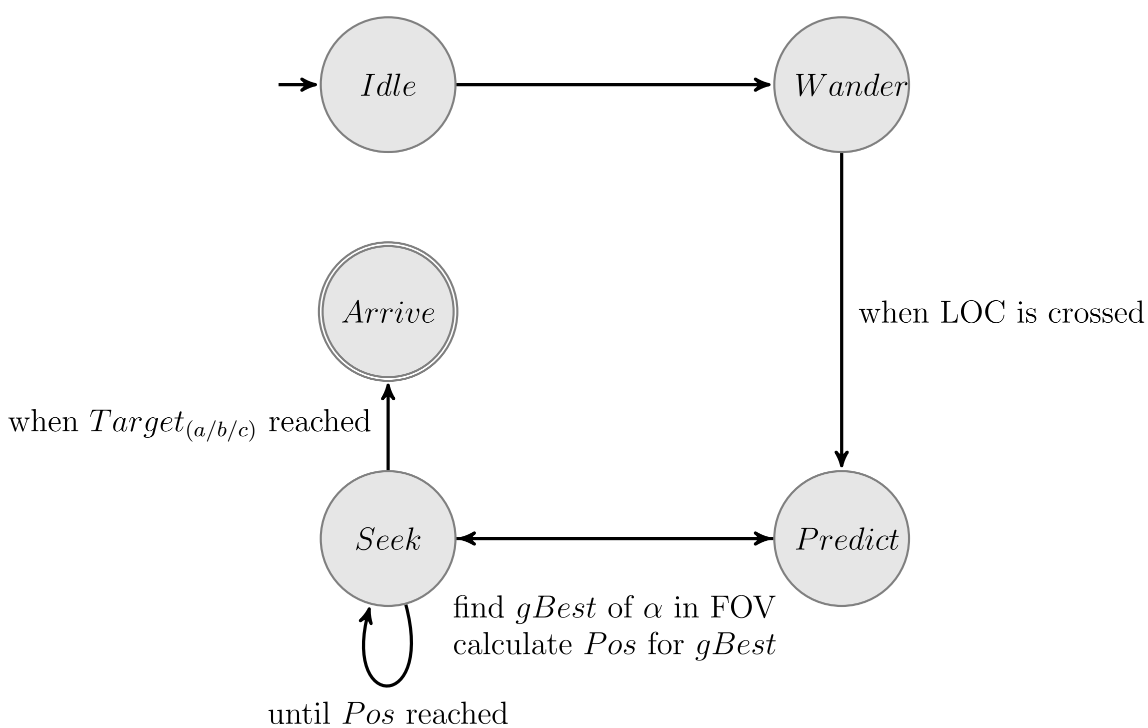


Figure 4.5: State of an agent in the proposed model.

4.2.4 Agent Character

Initially, every agent is defined with *None* character, once the movement starts and an individual is in *Predict* state it determines the neighbourhood around its communication radius and the character is determined for an agent.

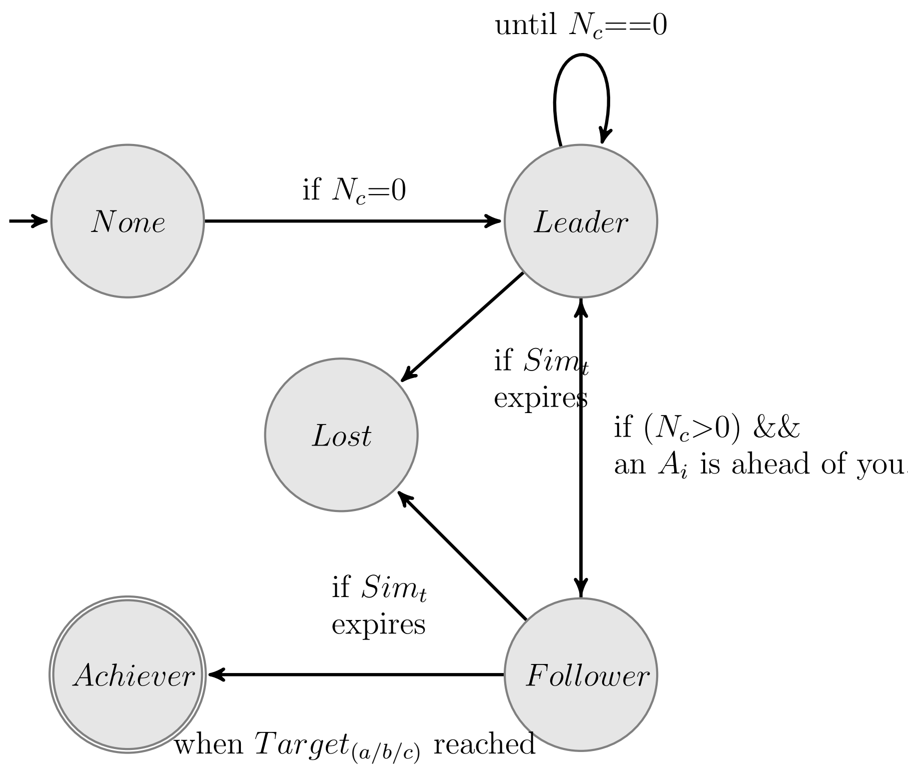


Figure 4.6: Characters of an agent in the proposed model.

If the neighbour count N_c is equal to zero, then the character is *Leader*, if the N_c is greater than zero and any of those neighbours are ahead of an individual agent's position, then the individual agent is set to the *Follower* character. The N_c value determines and switch the agent Character between *Follower* and *Leader* state. Upon, reaching a target the character is defined as *Achiever*. The agents who could not reach any target in the duration of the simulation time are classified in the *Lost* state.

4.2.5 Predicted Position

In Figure 4.7, a complete 360 degrees radial FOV of an agent is shown.The blue arrow represents the heading direction of an agent in local space. The grey lines and the green circles are representing a directional angle α set based on a Narrow or Wide field of view. These are the points in world space of an agent. For each direction, the position is calculated using the parametric equation of a circle. Considering, a two dimensional Cartesian Coordinate System, where agent's position is *C(0,0)* and the Step radius S_r=2. The points in green will be calculated using the given equations of circle Eq. 4.1 and Eq. 4.2.

4.2.5.1 Step Radius

Every predicted position on the direction angle α within the FOV is calculated based on the step movement an can take. This step ahead variable is denoted as S_r. The calculated position is computed by this step value ahead of an agent's current local position. So, every agent moves based on its local position at an angle α, which is voted as best direction to take.

It is important to note that this step radius S_r should not be greater than the communication radius C_r, because if the predicted position goes beyond the neighbouring radius, the chances of collision increases within individuals that are near to eachother. The predicted position can be calculated based on parametric equation of the circle if radius and intended angle α is known [35].

4.2.5.2 Circle Equation

In Eq. 4.1 and Eq. 4.2 , the new point (P_x, P_y) is calculated given the position of agent which is (C_x, C_y) plus the step radius S_r representing the step ahead of the agent position intended to the directional angle α.

$$P_x = C_x + S_r * cos(\alpha) \tag{4.1}$$

$$P_y = C_y + S_r * sin(\alpha) \tag{4.2}$$

Furthermore, it is important to note that the computation of the position from the angle α is in the world-space rather then the local-space of agent. Because every agent after getting in the *Seek* state rotates towards the directional angle α in its local-space which results in the different directional angle α in world-space. So, if an individual i is rotated to 90 degrees, and then predicts a *pBest* as 45 degree in local-space, where as in the world-space the direction would be 135 degrees. Hence, the selection and computation of predicted direction is subjected to the world-space throughout this thesis context.

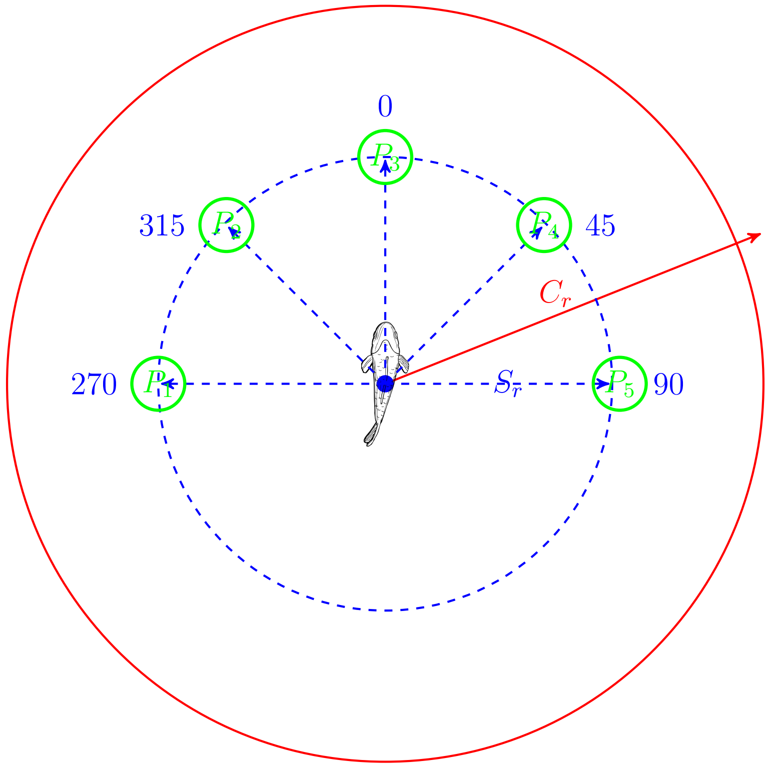


Figure 4.7: Narrow FOV: Predicted position from directional angle α based on Step radius S_r shown in blue dashed lines. The red solid circle and line shows the communication radius C_r.

4.2.6 Collision Avoidance

Every autonomous agent have a mechanism of avoiding obstacles and reaching out its target without any delays. In our model, the collision of agent is designed using Unity Physics Engine. Every agent has a Sphere Collider[1] attached to its body, which helps to keep it away from merging into other agent's mesh and also not bumping into the obstacles such a walls of arena. As the movement model is based on step wise predicted position. There was a need of more refinement for collision mechanism, often the predicted positions fall into the radius of another agent. To avoid such incidents to occur, the inverse of the heading direction of an agent moving is re-calculated.

4.2.6.1 Wall Avoidance

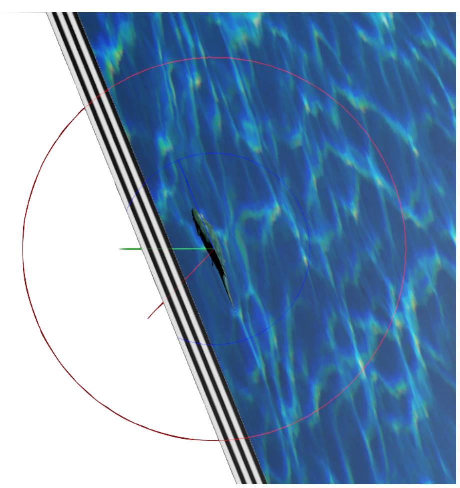
To avoid getting stuck in the wall in *Seek* state, an agent calculates before movement if the predicted position is colliding with any obstacle. If its a wall, then it calculates the inverse of angle α_i Eq. 4.3, which results in a behaviour of ping-pong Figure 4.9. Where agent tries to move to new inverse angle α_i and once reaching that point, predicts the best directional angle again to its known target. In Figure 4.9, the behaviour is shown with solid lines green and blue showing $R_{forward}$ and R_{force}, and the inverse angle R'_{force}.

[1]Sphere Collider:https://docs.unity3d.com/Manual/class-SphereCollider.html

The arc in orange shows the rotation of heading direction of an agent before moving to the new position.

To counter this issue, after re-calculating inverse of an angle. Then the mean of angles Eq. 4.18 is calculated between the α_p predicted angle for movement and the new α_i inverse angle. The new angle is the average heading direction which does not halt the movement of an agent. If the α_p is greater than 0 (zero) which means agent wants to move right in global-space then the 180 is added to the α_p, otherwise is it subtracted if the α_p is less than 0 (zero) and agent wants to in left direction.

$$\alpha_i = (\alpha_p + 180) \ mod \ 360 \tag{4.3}$$



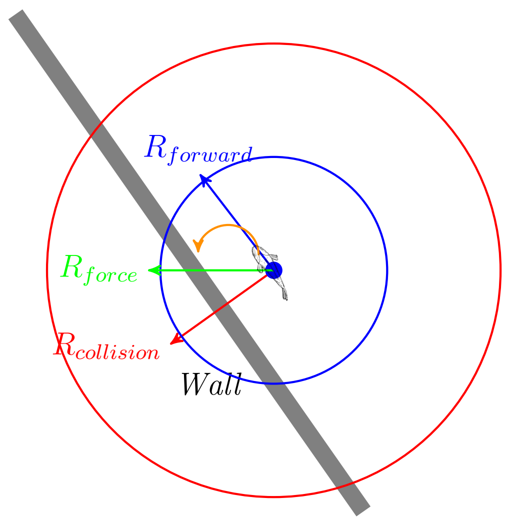


Figure 4.8: (left) Wall Avoidance of Fish Agent from the Simulation (right) Drawing depicting the same scenario with Rays information.

In Figure 4.8 on left the scenario of agent with wall avoidance is shown from simulation snapshot. On right a sketch of how it is working is drawn for better understanding. In right, an agent at a simulation time-step is trying to move towards the predicted direction angle shown in green ray labelled as R_{force}.

The red $R_{collision}$ detects the obstacle ahead where as $R_{forward}$ shows the heading direction of an agent in local-space. The position at that angle is outside the bounds of wall shown in grey colour. The orange arc shows that agent before translating, rotates from its forward $R_{forward}$ to the R_{force}.

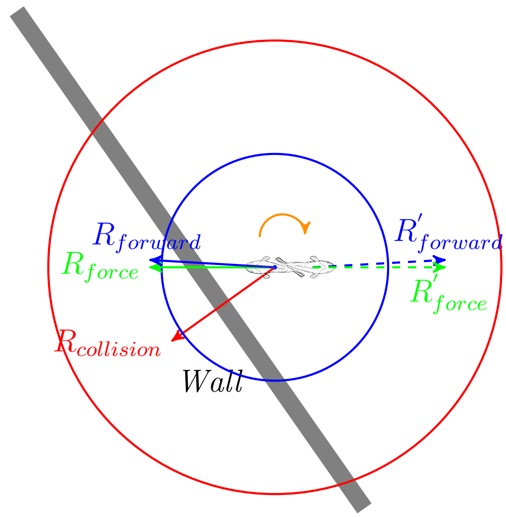


Figure 4.9: Wall Avoidance: Fish agent in a ping-pong state cause of inverse directional angle.

4.2.6.2 Agent Avoidance

To avoid any other agent is rather simpler then wall, because every agent has a collision bounding box which does not let any other agent to penetrate with each-other. The collision here with other agents is rather caused by the forces being cancelled out. Based on the movement at each time with predicted positions. Each agent tries to steer towards its preferred next position, but it is most likely that they will come in the way of other agents who are also moving towards their preferred position. If those positions are opposite to each-other, both agents apply force to move and hence, the force is equal to zero and no movement at all.

In Figure 4.10, the two agents are applying force in the opposite directions which is the direction chosen as *gBest*. The agent on left is applying force R'_{force} and agent on right is applying R_{force}. But as both are applying force at same time with same value. It is cancelled out and hence it results in no movement at all for these agents.

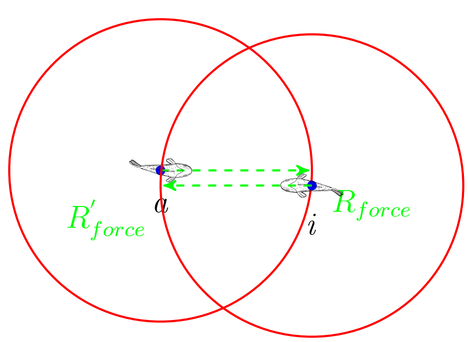


Figure 4.10: Collision with other agents while moving in opposite direction to eachother.

4.2.7 Rank

Agents reaching target are ranked based on their arrival time at any target. The first one to reach any target will be ranked as one and others follow the count respectively. The ranking of the agents is a global list and it helps in determining which agents are most likely to reach a target sooner. It is assumed that an agent who is spawned at a position near to the LOC is most likely to get a higher rank (highest rank is one). The start position of the agents spawning in the environment is always random.

4.3 Decision Making Model

In our proposed model, we use the opinion based design approach [61]. The opinion of all the agents in the neighbourhood are rated, and the majority opinion by decision makers is selected. The selected opinion represents the global best opinion of all the agents within communication radius.

In the work of Valentini et al. the rating of opinion is done with WVM. Where the self-organised robots are surveying sites, and their quality is rated to find the one best site with majority votes[60–62]. Instead of sites, we evaluate on each time-step the direction to take by an agent and its neighbourhood. In a swarm of fish, it is not only the individual decision making, but a fish always try to stay closer to its school, to be safe from predators. The essential factor for moving in the swarm is the cohesion with the social group. In our model, the MCDM problem has the two criteria which are conflicting with each other. We want to calculate the minimum distance to the known target, and if an agent is not alone, then the agent has to check with its neighbours if the decision taken is accepted by the majority as well. We are using the opinion based approach with basic voter model to rate the opinions on which direction to take to reach a target.

The criteria for the proposed model are the distance and cohesion, where the alternatives are defined as directions in the FOV of an agent. The proposed model first uses a prediction based approach to calculate the positions for all the alternatives in the FOV of an agent and then finds the best alternative for an agent based on first criteria (distance to target). In every physics time step, the best alternative is selected based on the first criteria of minimum distance to the known target. The selected alternative is then rated as the best opinion of the agent with a value of 1 (one) and rest of alternatives are rated as 0 (zero).

For the second criteria, every agent shares its opinion with other agents in the neighbourhood and the alternative which gets the majority rating is selected as the global best for that local flock. This global best alternative is then the heading direction of the local flock who are sharing social information. The position to move is calculated for the global best alternative, and the force is applied to an agent body to move in that calculated position (from heading direction) while rotating smoothly in that direction first. After reaching the predicted position, the next move is calculated similarly until an agent has reached any target.

4.3.1 Multi-Criteria Decision Making

The two criteria of our model are;

1. Minimum distance to the target as *pBest*
2. Majority opinion on the heading direction α within neighbourhood as *gBest*

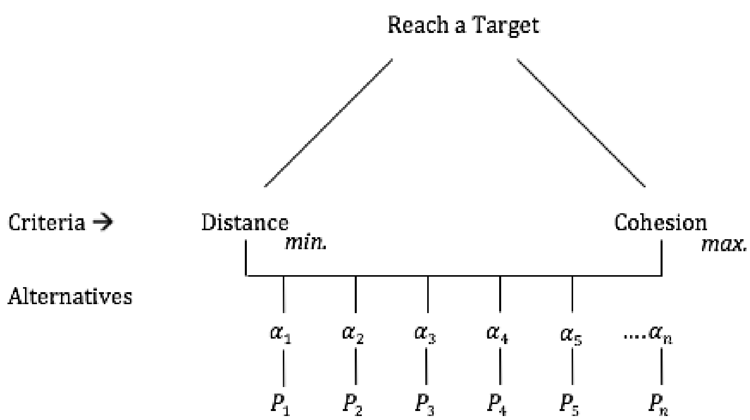


Figure 4.11: Our proposed model criteria and alternative representation tree; The two criteria are of distance to target and cohesion. The α is representing the set of alternatives and P as the position of each α.

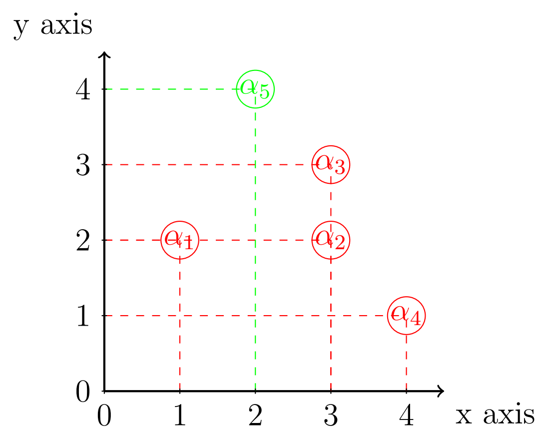


Figure 4.12: The conflicting criteria; y-axis represents the cohesion on rated angle α and x-axis represents the minimum distance to known targets on an angle α.

In the Figure 4.12, the criteria are shown with arbitrary values to show the ratings on y-axis and distance to target on the x-axis. The best directional angle α in the given plot is α_5 which has a minimum distance to a target and majority rating. Considering our experiment with the multi-target environment with the multi-agent system; an agent has to decide based on the social information if its neighbour count is more than zero at a time-step. Hence, the multi-criteria problem has to be divided into single-objectives, and then it can be solved one after another to achieve the intended result for our experiment.

In the table given below, Table 4.1 the arbitrary data of an agent with known targets is shown, where α represents NarrowFOV as shown in the figure Figure 4.13 and each column for α represents $\{\alpha_1, \alpha_2, ..., \alpha_n\}$ the calculated distance to the given Target. The *pBest* is calculated based on pair-wise comparison in between all distances. In the next table Table 4.2, the cohesion with the neighbours N is shown with rating on each direction.

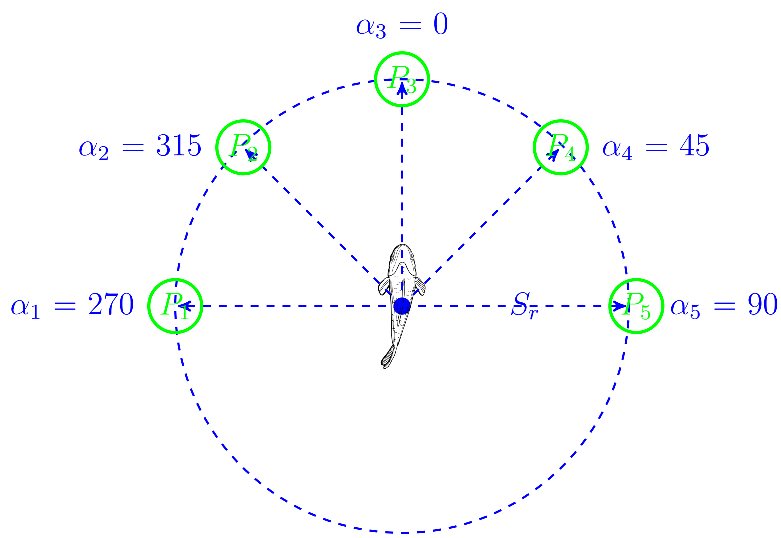


Figure 4.13: Narrow FOV: Predicted position from directional angle α based on Step radius S_r shown in blue dashed lines. The red solid circle and line shows the communication radius C_r.

On every directional angle α find minimum distance to Targets					
Target	α_1	α_2	α_3	α_4	α_5
A (Trained)	0.2	3.0	0.5	1.0	1.5
B (Not-Trained)	0	0	0	0	0
C (Consensus)	2.0	1.2	0.5	1.5	0.95
minimum distance	0.2	1.2	0.5	1.0	0.95
pBest with minimum distance get α_i^R	1	0	0	0	0

Table 4.1: Agent A: Calculate predicted positions at every angle α_i to find distance to targets and then rate the one with minimum distance as *pBest* α directional angle

Rating on directional angle α_i to find Cohesion with neighbours					
	α_1	α_2	α_3	α_4	α_5
Agent A (rated)	1	0	0	0	0
# of neighbours who rated for same predicted position (N=10)	2	3	1	4	0
α_m^R = sum of α_i^R / (N+1)	0.272	0.272	0.090	0.363	0
gBest = maximum (α_m^R)	0	0	0	1	0

Table 4.2: Agent A: Finding the *gBest* out of the rated angle α_i based on the majority rating *pRate* from neighbours.

We propose a mathematical model which handles both criteria one by one based on personal and social information of an agent. The initial distribution of agent population in the two-dimensional space $\mathbb{R}^2$ is randomised in the Start Arm. The proposed model shows a self-organised behaviour of an agent f at time-step t with neighbourhood N. This agent f considers opinion of every other agent in neighbourhood before making decision to move in $\mathbb{R}^2$. The equations Eq. 4.5 and Eq. 4.6 shows the calculation of a predicted position based on the every direction in the FOV. The α represents a directional angle, where i denotes the index of α starting from 1 to n i.e. $\{\alpha_1, \alpha_2, ..., \alpha_n\}$. For every α_i the intended position is calculated with respect to the agent current position $P_c^f(t)$ where $P_x^f(t)$ and $P_y^f(t)$ represents the x and y axis of the position of agent f at time-step t in $\mathbb{R}^2$.

At time-step *t=0*, where $P_c^f(t) \in \mathbb{R}^2$;

$$P_c^f(t) = (P_x^f(t), P_y^f(t)) \tag{4.4}$$

At time-step *t+1* for each α_i calculating P_x^f and P_y^f;

$$P_x^f(t+1) = P_c^f(t) + S_r * cos(\alpha_i) \tag{4.5}$$

$$P_y^f(t+1) = P_c^f(t) + S_r * sin(\alpha_i) \tag{4.6}$$

For each α_i the predicted position $P_i^f(t+1) \in \mathbb{R}^2$;

$$P_i^f(t+1) = (P_x^f(t+1), P_y^f(t+1)) \tag{4.7}$$

The equation Eq. 4.7, shows the calculated predicted position at each direction in the FOV. The index i in the position $P_i^f(t+1)$ represents the respective the α_i direction. Next, in the following equations Eq. 4.8, Eq. 4.9 and Eq. 4.10 the euclidean distance to known Targets A, B and C for each predicted position $P_i^f(t+1)$ is computed where $P_A^{T_r}$ represents Target A position in $\mathbb{R}^2$ and $dist_i^A$ represents the distance calculated in each

α direction. Likewise, $P_B^{T_r}$ for Target B and $P_C^{T_r}$ for Target C. The distances calculated are represented as $dist_i^B$ and $dist_i^C$ respectively.

$$dist_i^A = (P_i^f(t+1), P_A^{T_r}) \tag{4.8}$$

$$dist_i^B = (P_i^f(t+1), P_B^{T_r}) \tag{4.9}$$

$$dist_i^C = (P_i^f(t+1), P_C^{T_r}) \tag{4.10}$$

According to the first criteria of finding the α_i which gives the minimum distance to the known target. We use pair-wise comparison to iterate on the list of distance for each target from each direction as shown in equations Eq. 4.8, Eq. 4.9 and Eq. 4.10. The personal best α direction is selected out of all distances. The given equation Eq. 4.11 returns the index of α direction on which the minimum distance is achieved to a target.

$$pBest = \underset{\substack{1 \le i \le n \\ k \in (A,B,C)}}{\arg\min} \, (min(dist_i^k)) \tag{4.11}$$

The α direction at $pBest$ index is rated as 1 (one) and others are rated as 0 (zero). The rating on each α is represented as α_i^R;

$$\alpha_i^R = \begin{cases} 1 & \text{if i} = pBest \\ 0 & otherwise \end{cases} \tag{4.12}$$

The mean proportion of majority rating on a direction α is represented as α_m^R, it is calculated based on the opinion of every agent f in the neighbourhood N divided by N+1, where plus 1 (one) represents the opinion of an agent who is making the decision.

$$\alpha_m^R = \frac{\sum_{i=1}^{n} \sum_{f=1}^{N} (\alpha_i^R)}{(N+1)} \tag{4.13}$$

According to second criteria, the maximum cohesion from the majority rated direction α_m^R is selected if the mean proportion value of $\alpha_m^R > 0.5$, it is then selected as the $gBest$. Otherwise the mean μ of all directions which have rating > 0 is computed to get an average heading direction;

$$gBest = \begin{cases} \alpha_m^R & \text{if } \alpha_m^R > 0.5 \\ \mu \; \forall \; \alpha_m^R > 0 & otherwise \end{cases} \tag{4.14}$$

The selected direction α at $gBest$ is then used to calculate the next position to move by every agent in the neighbourhood N based on their local current position $P_c^f(t)$. The position is calculated based on the equations Eq. 4.15 and Eq. 4.16 with new direction as α_{gBest}, the computed x and y represents the next position to move based on equation Eq. 4.7.

$$P_x^f(t+1) = P_c^f(t) + S_r * cos(\alpha_{gBest}) \tag{4.15}$$

$$P_y^f(t+1) = P_c^f(t) + S_r * sin(\alpha_{gBest}) \tag{4.16}$$

Rating threshold of α

The majority rating from Eq. 4.13 is computed if the N is greater than zero. If there are no neighbours around agent in the C_r then its *pBest* is the *gBest* direction. Otherwise, the rating of neighbours matters to take collective decision. The given equation Eq. 4.13, states the minimum threshold for the selection of majority rating.

$$rating_{min} = \frac{\frac{N+1}{2}}{N+1} \tag{4.17}$$

The minimum rating threshold is in range of 0 to 1. If the rating α_m^R of an angle α calculated in Eq. 4.13 is more than 50 % (0.5) of the neighbours N who have voted for same α consider it to be the *gBest*. Otherwise, take the mean of all angles as shown in above equation Eq. 4.18 to find an average heading for all agents within the neighbourhood. The plus one in the equation above is representing the agent who is making the decision based on cohesion with the social group

Mean of angles

Mean of all the rated angles with the value greater than 0 (zero) is calculated based on the equation below. Where n represents the total number of selected α which has a rating greater than zero, the j represents the index of α direction.

$$\alpha_{mean} = atan2(\sum_{j=1}^{n} sin\alpha_j, \sum_{j=1}^{n} cos\alpha_j) \tag{4.18}$$

4.3.2 Process Flow

The flowchart in Figure 4.14 explains the overall process of the proposed model. The process shows a general overview of the process with every node having more detailed sub-processes in itself. This flowchart is based on the agent states throughout the process and how they switch based on different parameters. The key nodes in the process model are;

1. Initializing simulation parameters, selection of environment, simulation test cases (mixed or unmixed), group type count, FOV, total iterations and time.
2. Spawning of agents in the environment.
3. Agent specific parameters, defining C_r and agent avoid distance.
4. Initial wandering of agents in the spawning area.

In the Figure 4.14 on next page, the light grey nodes are the initial setup for the simulation run, where the agent-specific parameters, and time can be set. The light red diamond show the decision-making points, which leads to different results.The light yellow nodes are the agent processing units, starting from the prediction of positions on directions, to the calculating distance to targets, to the selection process of choosing the best direction based on objectives and finally seeking the predicted position until any target has reached. The arrive state is represented in green which is the last processing state of an agent where the loop ends for that agent.

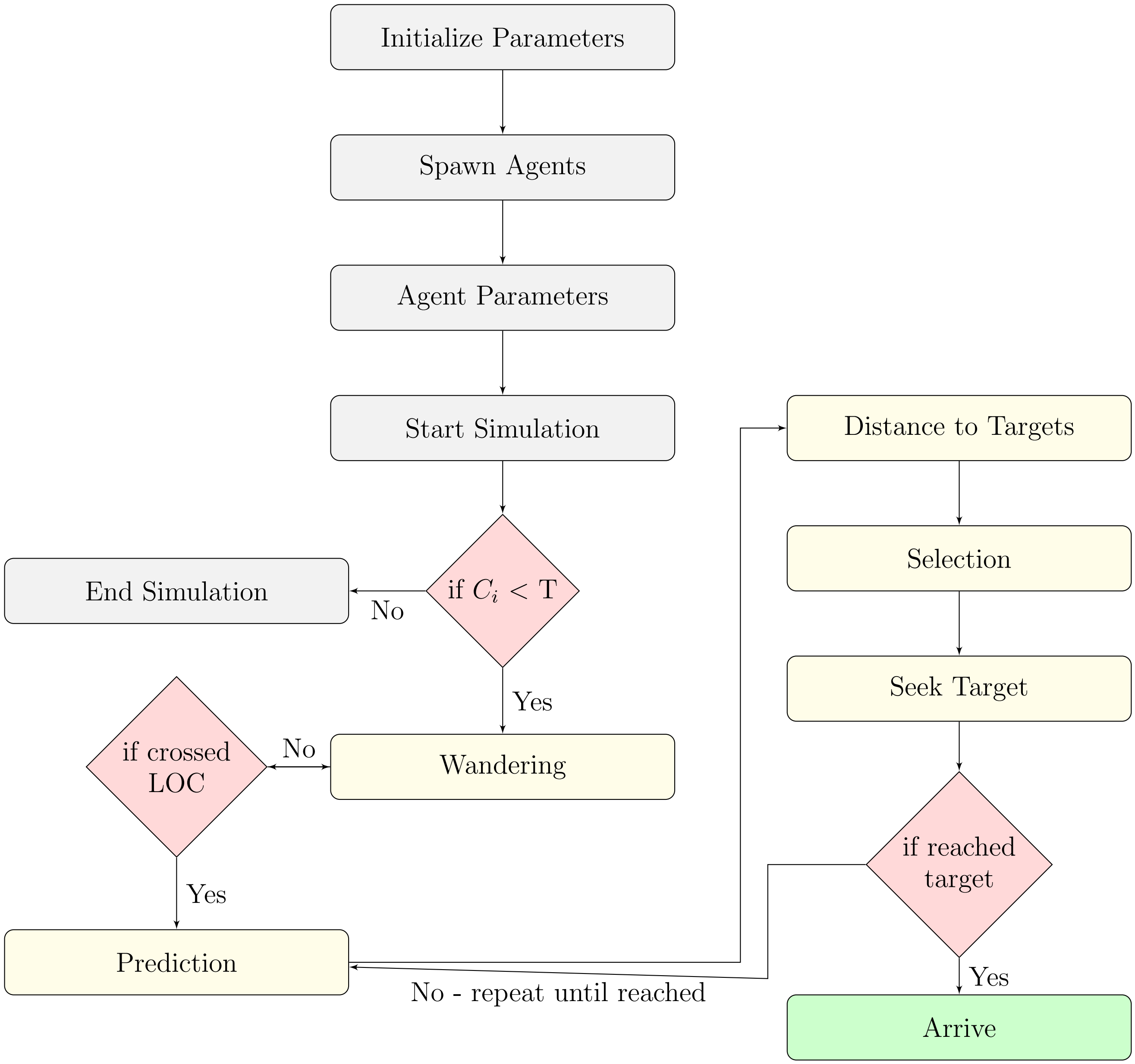


Figure 4.14: An abstract overview of the whole process through different states of an agent. Where C_i represents the current iteration counter and T represents total iterations. LOC is line of control for an agent to get activation of target seeking behaviour.

4.3.3 Voter Model

The decision making based on prediction based approach is shown in the given flowchart in Figure 4.15. When the agents passes the LOC, the process of predicting next position to take starts. The key nodes in the voter process model are;

1. Calculating distance to known targets from positions on each α in FOV
2. Selecting minimum distance to target and its respective α direction
3. Defining agent's character based on N neighbour count
4. If Leader, then go in the α direction as *gBest* which is equal to *pBest* in this case.
5. If Follower; find the majority rated direction α as *gBest*
6. Seek the next position calculated from *gBest* direction
7. Repeat the process until any target has reached.

In the prediction state, the first step to process is the calculation of position on the directional angle α given in the FOV (Narrow = 180° and Wide = 270°). The pool of position represents a Vector3 point respective to the agent's coordinates. It is a step ahead movement in the direction of an agent.

For each position distance to targets known is calculated, and the one α which gives the minimum distance out of all targets is selected as *pBest*, based on personal information of an agent. In the decision state, it is checked if there are neighbours of an agent; then the rating is shared among the social group within radius C_r and the majority best α is selected. The *gBest* is now the heading direction of this local flock who shared their opinions. The next position to move is calculated on this α and agent moves towards it. If there are no neighbours around, then the agent would take a character of a LEADER and move towards the position in the direction selected.

In the next chapter, the model implementation in a simulation engine is discussed with the algorithms developed based on the model presented in this chapter.

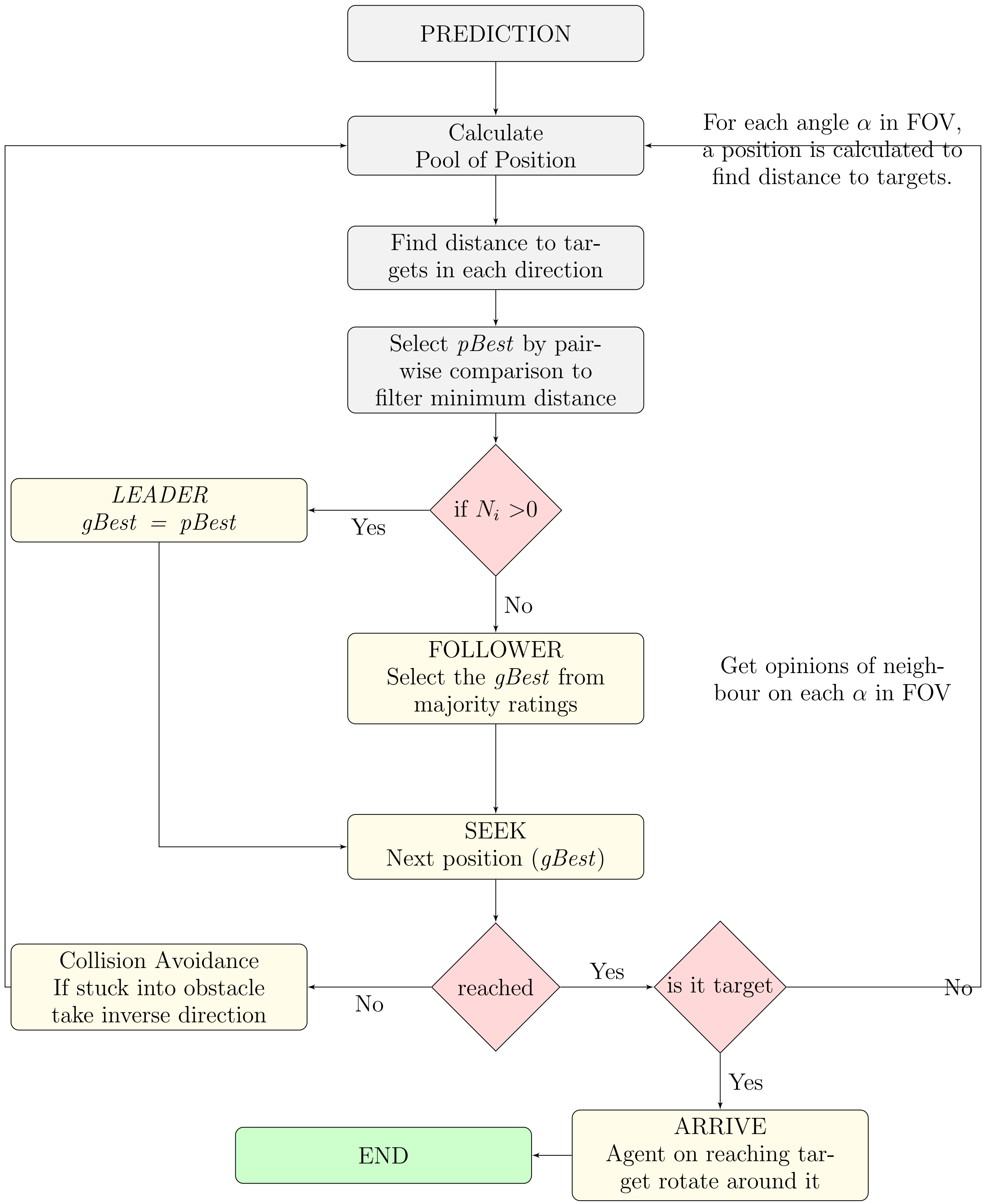


Figure 4.15: An agent prediction based voter model to choose next best direction to move. Where N_i represents the neighbours of an individual agent; *pBest* is the personal best of an agent and *gBest* is global best within neighbourhood.

5. Simulation Model

In this chapter, the implementation of the proposed model presented in the previous chapter is discussed in detail, following the simulation environment and algorithms developed to achieve results. The simulation is designed and developed using a game engine called Unity3D[1]. The 3D models used in the design of simulation environment are Unity primitives assets. The proposed model consisted of designing following major tasks:

1. A multi-target environment design.
2. The spawning of agents into the environment.
3. An agent with a SOB with movement model and decision making to achieve consensus.
4. An agent collision avoidance mechanism.
5. A User interface (UI) to control parameters of simulation.

5.1 Simulated Environment

5.1.1 Design

The Figure 5.1, shows the simulation Environment 1 snapshot. It contains the multi-target environment with defined targets at the end of arms. The bottom left panel titled 'Experiment' is the parameter control UI, which helps to control the simulation features. The environment design consists of four rectangular-shaped regions referred as Arms as discussed in previous chapter. The arm on the left has the green textured floor and walls with vertical stripe texture in black and white, this arm consists of Target A.

The arm on the right has the blue textured floor with the horizontal stripes wall texture in black and white, this arm has Target B.

The third arm in the middle is called Consensus Arm which consists of the the floor from Target A and walls from the Target B and is called as Target Consensus (C).

[1]Unity Technologies: https://www.unity3d.com

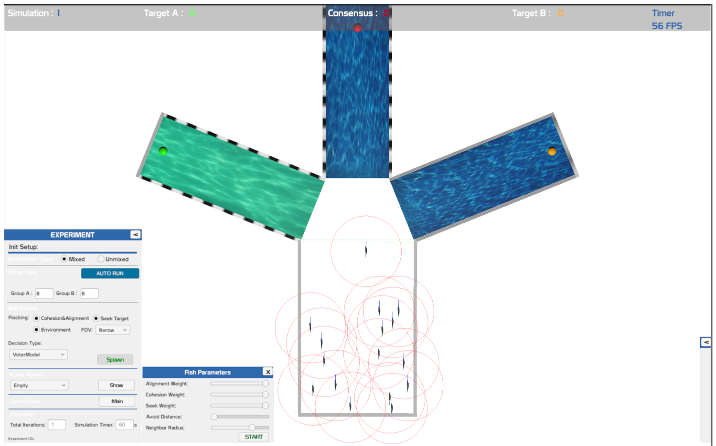


Figure 5.1: Top View of Environment 1 with 16 x agents spawned in the Start arm and UI parameters window with specified settings.

The point of interest is the middle arm, the Consensus Arm with target. In the experiment of mixed group, the agents should reach this middle arm, if successfully collective decision is made in the group.

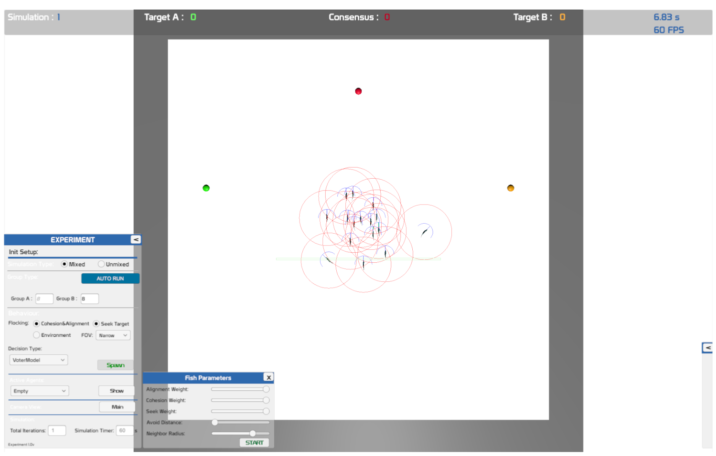


Figure 5.2: Top View of Environment 2 with 16 x agents spawned in the starting region, crossing LOC

The Figure 5.2 shows the top view of squared environment with boundary in grey colour. The agents spawned in the starting region are crossing the LOC to start process of reaching their preferred targets.

5.1.2 Parameters

The simulation environment contains the following User Interface (UI) parameters, which helps in testing out the simulation with different values:

Experiment

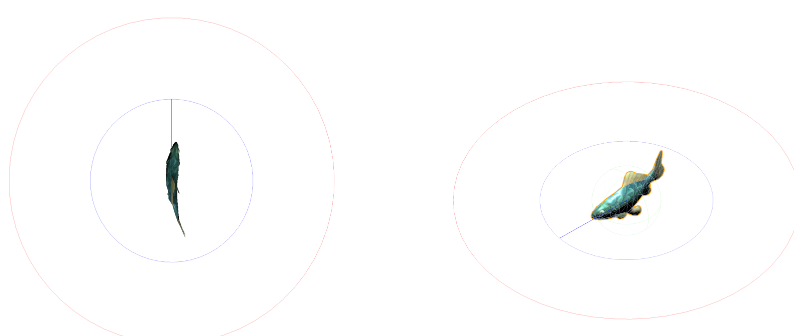
1. Simulation type (Mixed or Unmixed).
2. Group type agent count (A or B)
3. Select Environment 1 or 2.
4. Select Decision type (Our proposed model is labelled as Voter Model)
5. Set simulation time out.
6. Set simulation iterations run (for the same set of parameters).

Agent

1. Communication radius
2. Avoid distance

5.1.3 Agent 3D Model

In Figure 5.3, an agent model used in simulation is shown. It is a free three-dimensional (3D) low poly fish model from asset store of Unity. The model has a basic swim animation with it. The blue line shows the heading direction of fish, with two circular regions one representing C_r and other S_r as discussed in the previous chapter.



(a) (b)

Figure 5.3: Fish Agent 3D Model in simulation with (a) Top View (b) Side View. The red circle shows the communication radius and blue the step radius. A blue at front of fish is the heading direction (forward).

5.2 Movement Model

The movement model designed for the simulation is based on prediction based approach where each direction to take is evaluated first personally and also within neighbourhood of an agent. It is not a continuous model like BOIDs flocking [45] where cohesion and alignment is calculated based on position and direction of neighbourhood at every time-step. Instead, we are using a step wise approach to find best route to the target that is near to agent's current position.

The algorithm 1 shows how the position is calculated based on the direction α and S_r information. The simulation engine used for the development uses Quaternion system for the rotation of a three-dimensional (3D) object. The rotation of the agent is only needed in the y-axis as the movement is on the two-dimensional (2D) plane. The new position to move is calculated using the forward direction of the environment in world-space, the S_r value and the current position of an agent.

5.2.1 Position in 3D

Algorithm 1 Calculate position from angle with step radius S_r

function GetPosition(α)
  return $this.position + (Quaternion.Euler(0, \alpha, 0) * Vector3.forward * S_r)$
end function

The movement is updated in the fixed time-step controlled algorithm and once the selected best position is reached. The agent predicts the next one to move until it has reached a target. The algorithm 2 shows how an agent calculates its next best position from the pool based on its personal and social information. This algorithm is designed as a self-organized behaviour for an agent, hence has no dependency on the global movement of flock instead on every time step each agent decides for its own movement step.

The angle is represented as α in the algorithm context and the distance to targets is calculated as Euclidean distance. Due to the limited time and scope of this thesis, the movement of an agent is only on 2D plane x-axis and z-axis. Even though the environment is designed and developed in 3D space. A point in the environment is a Vector3 in $\mathbb{R}^3$, where the y-axis is set to a fixed value through out the simulation. Hence, resulting in the 2D movement in the arena.

The presented movement model in the algorithm 2 on next page, can easily be adapted to the 3D movement of agent in the arena.

Algorithm 2 Opinion based prediction model for agent movement

```
function NextPredictedPosition()
    pBest ← 0                                         ▷ personal best rated direction α
    gBest ← 0                                         ▷ global best rated direction α
    targetList ⟵ GetTargetList()
    N ⟵ FindNeighbours()                              ▷ N represents number of neighbours
    for each α in FOV do                              ▷ Find pBest direction α of an agent
        predPos ⟵ GetPosition(α)
        pBest ⟵ MinDistanceToTargets(predPos, targetList)   ▷ returns α as pBest
        ratingList ⟵ UpdateRating(pBest)              ▷ Update rating of a direction α
    end for
    if N > 0 then
        for each α in ratingList do
            cRating ← ratingList[α]
            for each agent in N do
                if agent.pBest is equal to this.pBest then
                    cRating ← cRating + 1
                end if
            end for
            ratingMean ⟵ cRating / (N+1)
            ratingList[α] ← ratingMean
        end for
        mRatedList ⟵ GetMaxRatedAngles(ratingList)    ▷ max. cohesion
        if mRatedList > 0 then
            gBest ⟵ MeanOfAngles(mRatedList)
        else
            gBest ← mRatedList[0]
        end if
    else
        gBest ← pBest
    end if
    return CollisionAvoidance(gBest)
end function
```

5.2.2 Neighbourhood

The neighbourhood topology as discussed earlier is based on two step process, one communication radius C_r and the FOV of an agent. If any agent lies in the C_r, it is further checked for the placement in the FOV of an agent it is around. This is calculated by taking dot product of positions of both agents. The agent is selected as neighbour, only if it falls into both C_r and FOV.

Also, the character of the agents are calculated based on the position an agent lies in the neighbourhood. If an agent is ahead of an individual agent in charge, it will be consider as Leader, otherwise Follower. The algorithm 3 shows how the neighbourhood list is refined for an agent while making decision for the next position to move.

The algorithm presented shows only the conditions for the Narrow FOV where the viewing range is 180 degrees. In the simulation testing, the condition is checked for both FOV ranges. The two step process of refining neighbours helps in achieving more promising results. The real fish is capable of seeing its neighbour if they are near or far, front or behind. The C_r value alters the result of an agent achieving consensus.

Algorithm 3 Finding neighbours and defining agent character

```
function FindNeighbours()
    character ← None
    headingDirection ← 0
    distance ← 0                                        ▷ Euclidean distance
    agentList ⟵ GetAgents()
    for each agent in agentList do                      ▷ All agents in simulation
        distance ⟵ EuclideanDistance(this.position, agent.position)
        if distance < C_r then
            headingDirection ⟵ DotProduct(this.position, agent.position)
            if headingDirection > 0 then
                N.Add(agent)                            ▷ Add agent into neighbours list
                if headingDirection >= 0.1 and headingDirection <= 1.0 then
                    character ← Follower
                else
                    character ← Leader
                end if
            end if
        end if
    end for
    return N                                            ▷ Neighbours of an agent
end function
```

5.2.3 Collision Avoidance

The Collision avoidance or separation from other agents is handled using Unity Physics Colliders. If all agents have colliders on their body they will not penetrate into body of other agents. The wall is avoided using inverse direction as collision technique. When an agent tries to move to a point that is behind the wall bounds, the direction an agent is trying it move is inverted into other direction. This prevents an agent from getting stuck to a wall.

In case of agent colliding with other agents, if the position to move is colliding with the radius of another agent, then both agents re-calculate, to find the next best position to move. In this way, the issue of getting stuck with another agent while travelling is resolved. The algorithm 4, shows how the above mentioned solution is implemented.

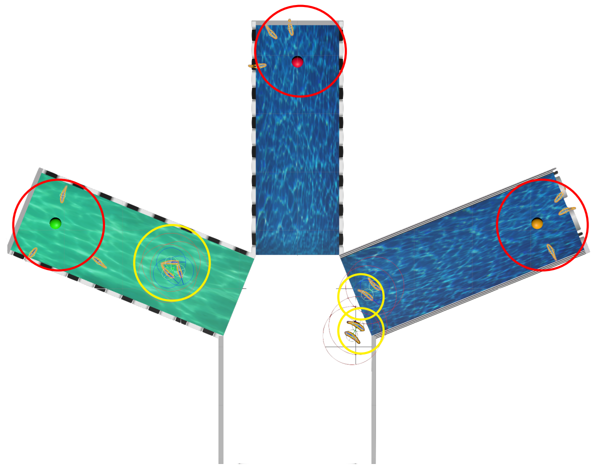


Figure 5.4: Agent Avoidance: Fish agent stuck because of *force=0* on moving in opposite direction to another fish agent

Algorithm 4 Checking Collision Avoidance on selected position

function COLLISIONAVOIDANCE(α)
    $nextPos \longleftarrow GetPosition(\alpha)$
    $rayDirection \leftarrow nextPos - this.position$
    $RayCastHit \longleftarrow Physics.RayCast(this.position, rayDirection, S_r)$
    if $RayCastHit$ `is true` and $TargetReached$ `is false` **then**
        if $RayCastHit.object$ `is a wall` **then**
            if $\alpha > 0$ **then**
                $\alpha_i \leftarrow (\alpha + 180) \mod 360$ ▷ α_i is inverse of an angle
            else if $\alpha < 0$ **then**
                $\alpha_i \leftarrow (\alpha - 180) \mod 360$
            end if
            $\alpha \longleftarrow MeanOfAngles(\alpha, \alpha_i)$
            $nextPos \longleftarrow GetPosition(\alpha)$
        else if $RayCastHit.object$ `is an agent` **then**
            $nextPos \leftarrow this.position$
        end if
    end if
    return $nextPos$
end function

In Figure 5.4, the yellow circled regions are showing the fish agents which are stuck with each other while trying to make their way towards their known targets. To counter such problem and keep simulation smooth and continues, the *Predict* state is reset for only these agents. Hence, each agent in a close radius decides again mutually where to move next, this solution keeps the flock cohesion intact. The red circled points in the figure shows the target points.

5.2.4 Moving Rigidbody

The agent is a Unity Physics Rigid-body which is moving with a certain velocity and has force applied in a specific direction. In order to move this agent body, it is called on fixed physics time-steps. The algorithm 5, shows how the agent body is moving towards certain position and rotating in the heading direction.

Algorithm 5 Moving agent body with force to a next predicted position

function MOVEAGENTBODY()
  $rigidBody \longleftarrow GetRigidbodyComponent()$
  $force \leftarrow Vector3.zero$
  $headingDirection \leftarrow NextPredictedPosition() - this.position$
  $force \leftarrow (force + headingDirection).normalized$
  $rigidBody.AddForce(force)$
  $this.rotation = Quaternion.LookRotation(rigidBody.velocity)$
    ▷ Rotating agent in heading direction
  $DrawRay(rigidBody.position, force * S_r, Color.green)$
    ▷ Draw a green ray in direction of force applied
end function

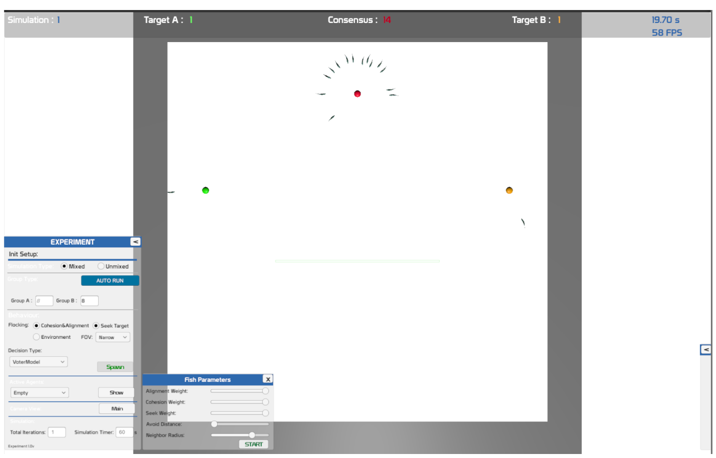


Figure 5.5: Top View of Environment 2 with 16 x agents reaching their preferred targets. On the consensus target majority of the agents have reached and are rotating around it as an Achiever.

The above Figure 5.5 shows the scene of environment 2 with agents who have reached Consensus target and how they are rotating around the target in a circular shape. The agents who reached Target A and B are the leaders who have given preference to personal information only and reached the known target without getting influenced by others.

The final running simulation model can be seen on following links; *(1)* Mixed group - 8:8 agents with Environment 1 and 2 Link1 , *(2)* Unmixed group - 4:12 agents with Environment 1 and 2 Link2, *(3)* Unmixed group - 16 agents with Environment 1 and 2 Link3 and *(4)* Mixed group and variation of C_r with Environment 1 and 2 Link4.

In the next chapter, the evaluation of the results is discussed in detail and how the combination of different parameters varies the consensus achievement of an agent.

6. Evaluation

In this chapter, the results from the simulation are discussed in detail, an overview of all parameters involved in results generation and how the results are affected by a specific trend. There are two major experiments conducted on group of agents to test how many agents can achieve consensus in a multi-target environment. Following are the two categories;

1. **Mixed group** - Two different set of agents with pre-defined memory of Target A and B. Total agents in one simulation run are 16, the test cases are developed with different ratios of agents from A:B.

2. **Unmixed group** - One complete set of agents with pre-defined memory of either Target A or B. Total agents in one simulation run are always 16.

6.1 Parameters

The following parameters are considered in formulating test cases to evaluate the results of simulation. There are total of 24 combinations for experiment on mixed group and 16 on unmixed group.

- **Environment:** There are two different environment designed for the simulation as discussed in previous chapters. Environment 1 with three-armed choice and Environment 2 with open arena and no walls in between the targets.

- **Field of View:** As discussed in the previous chapter, there are different directional angles α in a FOV which affects the selection of neighbourhood for an agent. Also, the α presents the set of alternatives for an agent to choose from. Hence, we tested this parameter with other variables as well to see how the trend will change if a FOV is selected as Narrow (180°) or Wide (270°).

- **Communication Radius C_r:** The communication radius range plays a crucial role in the decision making of an agent in a swarm. The larger the value of the radius, the more influence of social information on an agent. We tested with only two different values (0.4 and 0.8) from a range of 0 to 1.

- **Avoid Distance:** The agents avoid distance is not considered as parameter during the test cases. The value is fixed for all experiments, considering the environment scale and size of agent model, it is set to 0.1 as our best value. Although, if needed this can also be tested a parameter to see how the result is altered. The value of avoid distance should be less than the communication radius, because avoid distance is the radius of Physics Collider attached with every agent.

- **Trained Agents ratio:** Ever agent have a pre-defined memory of a Target A or B. In mixed group, this ratio is changed to see how it will affect the result of agents reaching on Target Consensus(C). For unmixed group, there is fixed number of 16 agents, either from Target A or B group type.

  For mixed group different ratio of trained agents are as listed;

  1. Agents trained with target A=4 and B=12
  2. Agents trained with target A=12 and B=4
  3. Agents trained with target A=8 and B=8

- **Simulation Time:** For the evaluation purpose, the maximum simulation time is set to 60 seconds. If all agents have reached a target then the simulation time stops and the next simulation iteration is executed. Otherwise, if agents still have not reached a target and simulation times expires. Those agents are are considered as Lost agents. The reason of choosing the 60 seconds time is on the basis of environment scale. On average we have observed that an agent travel time to reach any target is approx. 30 seconds. Hence, 60 seconds is an ideal double time for agents to make decision of reaching any target.

- **Simulation Iterations:** In our evaluation, for all experiments and combinations each simulation set has total 25 iterations. At the end of each simulation set, the mean of all agents who reached targets and ratio of agents reaching a specific target is computed.

<table>
<tr><th>Parameters</th><th colspan="2">Values</th></tr>
<tr><td>Experiment</td><td>Mixed</td><td>Unmixed</td></tr>
<tr><td>Environment (Env)</td><td>1</td><td>2</td></tr>
<tr><td>Field of View (FOV)</td><td>180°</td><td>270°</td></tr>
<tr><td>Communication Radius (C_r)</td><td>0.4</td><td>0.8</td></tr>
<tr><td rowspan="3">Ratio of agents (A:B)</td><td>4:12</td><td>A = 16</td></tr>
<tr><td>8:8</td><td rowspan="2">B = 16</td></tr>
<tr><td>12:4</td></tr>
</table>

Table 6.1: Parameter with their respective values for each simulation run.

The Table 6.1 shows the summary of all parameters involved in the test cases and their respective values. The values are used to create test cases for evaluation purpose which are discussed in the next section.

6.2 Experiments

6.2.1 Mixed group

The first experiment is of the mixed group where agents from both group types are part of the simulation. In the Table 6.2, all the possible test cases for the mixed group are given with their specific values. These cases are further tested on Environment 1 and 2 separately to observe, how much the result alters because of the environment change. The results are shown for Environment 1 in the Figure 6.1, Figure 6.2 and Figure 6.3 respectively. Likewise, the results for Environment 2 are shown in the Figure 6.5, Figure 6.6 and Figure 6.7 respectively. We will discuss results from each environment separately in detail. The mean of agents from type *GroupA* and *GroupB* is represented in plots with colour code of orange and grey respectively. The mean of groups together is labelled as *Both* and is in blue colour.

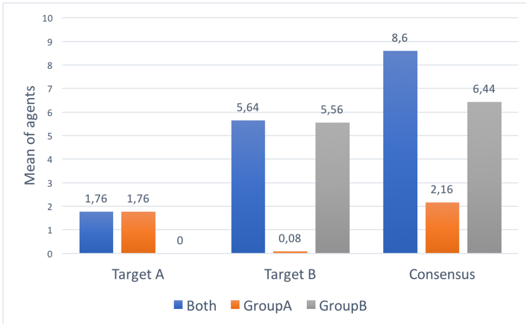
Case no.	**Ratio A:B**	C_r	**FOV**
1	4:12	0.4	180°
2	4:12	0.4	270°
3	4:12	0.8	180°
4	4:12	0.8	270°
5	8:8	0.4	180°
6	8:8	0.4	270°
7	8:8	0.8	180°
8	8:8	0.8	270°
9	12:4	0.4	180°
10	12:4	0.4	270°
11	12:4	0.8	180°
12	12:4	0.8	270°

Table 6.2: Mixed group with all possible cases based on parameter settings. The ratio of agents from each group type A:B, FOV and C_r. These cases are evaluated for Environment 1 and 2 separately.

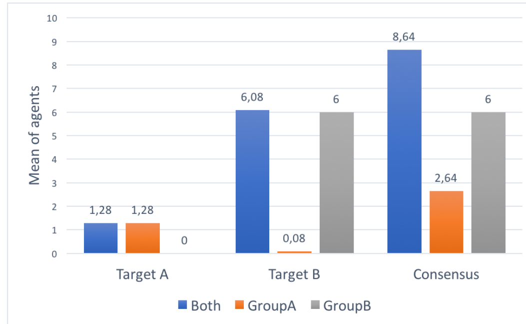
6.2.1.1 Environment 1

The plots from Figure 6.1 represents cases from 1 to 4 with ratio of 4:12 of type A and B agents respectively. It is clearly evident from the result of this figure that more than 50 % of the total agents always reach consensus regardless of the parameter settings. The value of *Both* represents agents type A and B and it is greater than 8.5 in all cases. The ratio of agent shows that more agents are from group type B, and the result of these 1-4 cases shows approx. an equal amount of type B agents reach Consensus and the value is greater than 6.0 for *GroupB*.

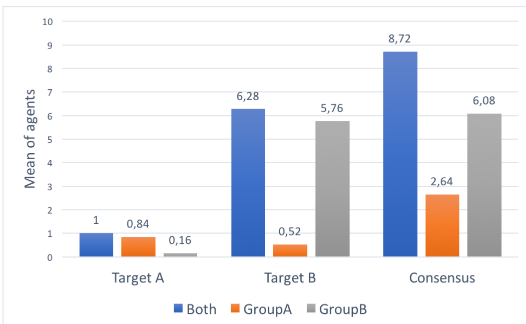
The other factors which increases the result on Consensus target is the C_r which changes between Case 1 to 3 and Case 2 to 4. So, it can be said from the analysis of these cases, that the best result on Consensus is achieved on Case 4 with $C_r = 0.8$ and FOV = 270°.



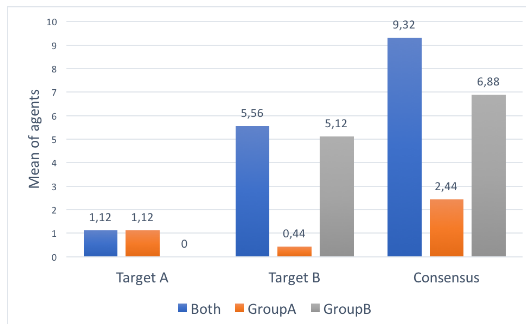
(a) Case 1



(b) Case 2



(c) Case 3

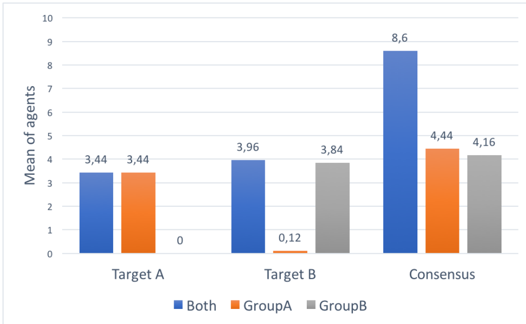


(d) Case 4

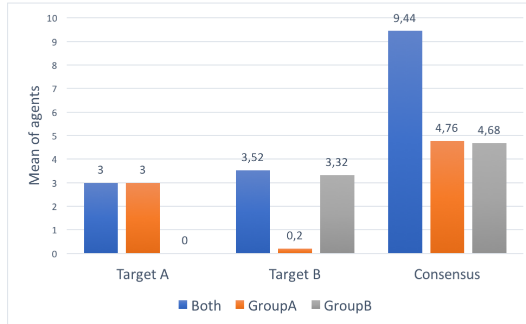
Figure 6.1: Mixed group with Environment 1; results showing $\bar{x}$ of agents after 25 simulations run for Case 1 to 4 with ratio 4:12. Each case represents a distinctive ratio of how many agents from group type A or B have reached Target A, B and Consensus.

In the Figure 6.2 on the next page, the figure represent cases from 5 to 8 with ratio of 8:8 of type A and B agents respectively. These cases are more relevant to the actual experiment results of MiE. The equal ratio of agents from both group type shows interesting results. It is evident that more than 50 % of the total agents always reach consensus and the ratio of agents on Consensus is approx. equal from both group types. The reason for the equal ration on consensus is because of the fact that our both type of agents have pre-defined memory of Consensus target as well. Since, we did not use the visual cues and the learning, our proposed model relies on global position of targets as information in agents brain.

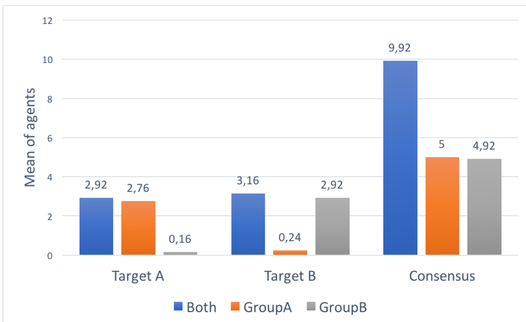
In the Case 7, the value of *Both* agents on Consensus has reached 9.92 which is in comparison to other cases from this ratio is a higher value. This case has parameter setting of $C_r = 0.8$ and FOV $= 180°$, which are different from Case 4 (ratio 4:12) in FOV. So, at this stage we cannot generalize that only with maximum values of C_r and higher range of FOV more consensus can be achieved.



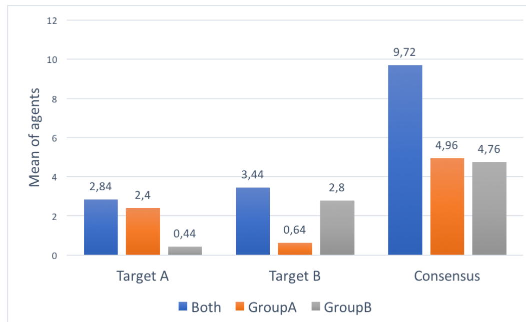
(a) Case 5



(b) Case 6



(c) Case 7

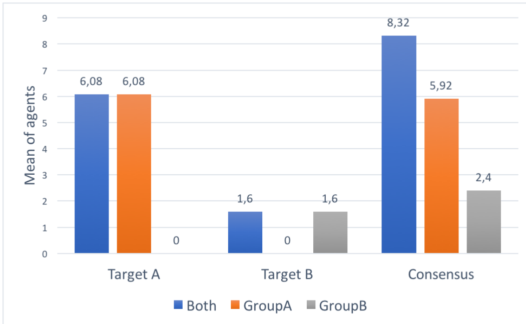


(d) Case 8

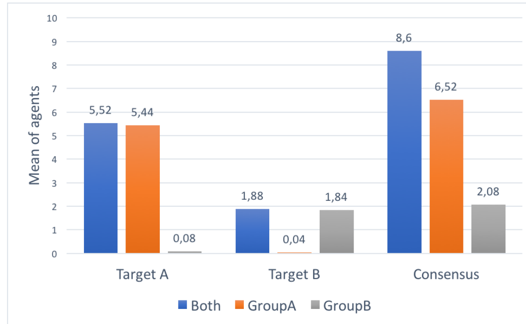
Figure 6.2: Mixed group with Environment 1; results showing $\bar{x}$ of agents after 25 simulations run for Case 5 to 8 with ratio 8:8. Each case represents a distinctive ratio of how many agents from group type A or B have reached Target A, B and Consensus.

In the Figure 6.3 on the next page, the plots represents cases from 9 to 12 with ratio of 12:4 of type A and B agents respectively. The results from these plots show the inverse of the results from Figure 6.1 of 4:12 ratio. The overall result of the Consensus is still more than 50 % of the total agents and the ratio of agents from *GroupA* is greater than 6.5 on Consensus target.

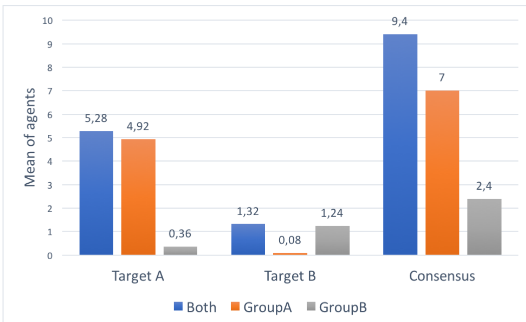
In the Case 11, the value of *Both* agents on Consensus has reached 9.4 which is higher mean value than other cases from the same ratio. The parameters for Case 11 are C_r = 0.8 and FOV = 180°, which is in comparison with Case 4 (ratio 4:12) are different in FOV. But the communication radius is constant in all cases which has resulted in higher mean at Consensus (Case 4-7-11). Hence, we can imply that with higher value of C_r, the mean at Consensus increases because the more agents opinion influences the decision-making.



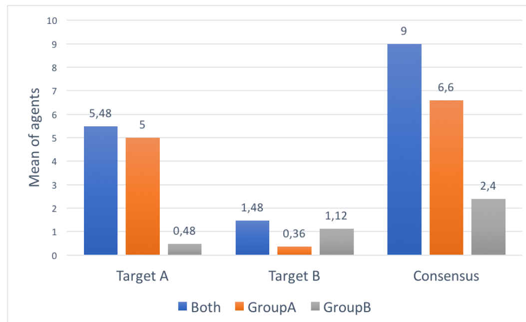
(a) Case 9



(b) Case 10



(c) Case 11



(d) Case 12

Figure 6.3: Mixed group with Environment 1; results showing $\bar{x}$ of agents after 25 simulations run for case 9 to 12 with ratio 12:4. Each case represents a distinctive ratio of how many agents from group type A or B have reached Target A, B and Consensus.

To evaluate further the test cases for Environment 1, we calculated the standard error for our sample mean data [7]. The next Table 6.3 shows the Standard deviation (SD) σ and Standard error mean (SEM) $\sigma_{\bar{x}}$ for all cases. The results of SEM from the table are plotted in the Figure 6.4 for Environment 1. From our simulation results, the sample mean of agents $\bar{x}$ for each test case is always equal to 4, because the total number of agents is equal to 16 and they are distributed among characters (Achiever or Lost). The distribution is evaluated from the agents position at the end of simulation, whether an agent has reached any target (A,B and Consensus) or it is a lost agent. The Table 6.4 shows the example of Case 6 data on which mean $\bar{x}$, SD σ and SEM $\sigma_{\bar{x}}$ is computed.

To conclude, the overall results of Environment 1 with different parameter settings. We can say that the higher mean value is achieved with Case 4, 7 and 11 where the $C_r = 0.8$, but the FOV is either 180 or 270 degrees. Even with the closed boundary environment, with much collision avoidance with walls and distraction from the intended position. The results are higher at the Consensus target. Hence, the most important parameter for achieving higher mean is the C_r, which influences the agent decision making based on other opinions.

Case no.	SD σ	SEM $\sigma_{\bar{x}}$ $\pm$
1	3.867	1.934
2	4.052	2.026
3	4.182	2.091
4	4.283	2.141
5	3.534	1.767
6	3.937	1.969
7	4.20	2.10
8	4.098	2.049
9	3.862	1.931
10	3.828	1.914
11	4.242	2.121
12	4.051	2.025

Table 6.3: Mixed group with Environment 1 for all cases values of SD σ and SEM $\sigma_{\bar{x}}$ where sample mean $\bar{x}$=4

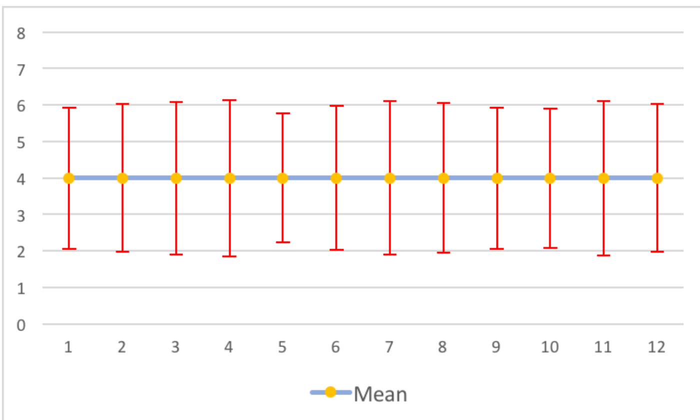


Figure 6.4: Mixed group with Environment 1; all cases SEM with $\bar{x}$ =4

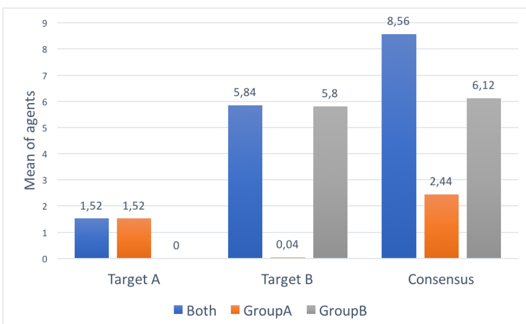
x	Category	Mean of agents
1	Target A	3.0
2	Target B	3.52
3	Consensus	9.44
4	Lost	0.04

Table 6.4: Sample mean data from Case 6 after 25 x simulation run the distribution of agents among category of Targets.

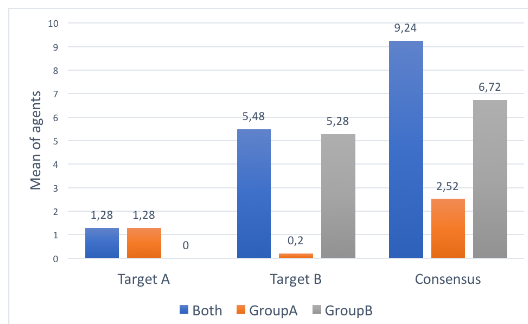
6.2.1.2 Environment 2

The plots from Figure 6.5 represents the Environment 2 test cases from 1 to 4 with ratio of 4:12 of type A and B agents respectively. The Environment 2 does not have closed boundary of walls in between targets instead it is an open square field with defined targets. The reason of testing with Environment 2 is to check, how much the collision avoidance mechanism is affecting the decision making of agents while steering.

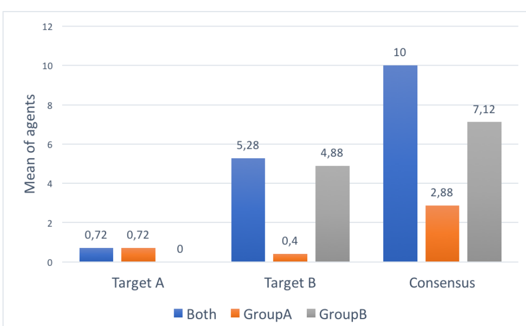
From the results in the plots, we can observe that the mean value of total agents reaching Consensus has increased in Case 2, 3 and 4 as compared to the results in Figure 6.1. Although, for the Case 1 with Environment 2 the mean value is less with 0.04 value. The mean value at Consensus is much higher in the Case 4, the reached value is 10.64 in *Both* type. The pattern here is the same as we have seen in the Environment 1 - Case 4, the C_r = 0.8 and FOV = 270° gives higher mean value at Consensus target.



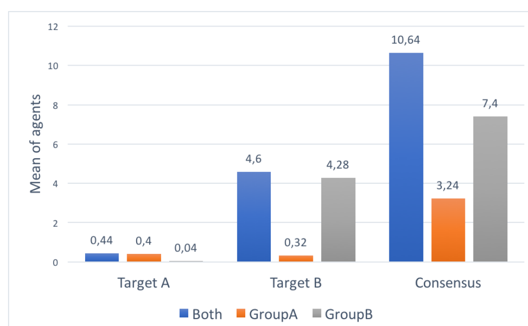
(a) Case 1



(b) Case 2



(c) Case 3



(d) Case 4

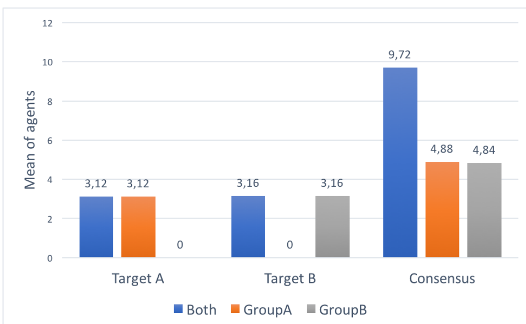
Figure 6.5: Mixed group with Environment 2; results showing $\bar{x}$ of agents after 25 simulations run for Case 1 to 4 with ratio 4:12. Each case represents a distinctive ratio of how many agents from group type A or B have reached Target A, B and Consensus.

In the Figure 6.6, the plots represents cases from 5 to 8 with ratio of 8:8 of type A and B agents respectively. These cases are the more relevant to the actual experiment results of MiE but with Environment 2 setup. The equal ratio of agents from *Both* group types shows a mean value of 11.03 at Consensus. The higher mean value reached is 13 on *Both* at Case 8 where C_r = 0.8 and FOV = 270°. In the Environment 1 with

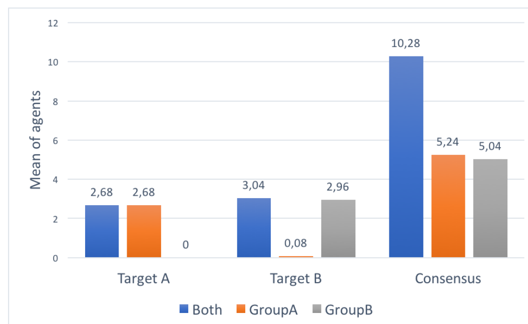
Case 8, we have seen the similar higher mean values as compare to others in the similar ratio.

When comparing results of Figure 6.5 with Figure 6.6 clearly shows an increase in the higher mean value at Consensus target. Also, the ratio of agents at Consensus target from type *GroupA* and *GroupB* is approx. equal.

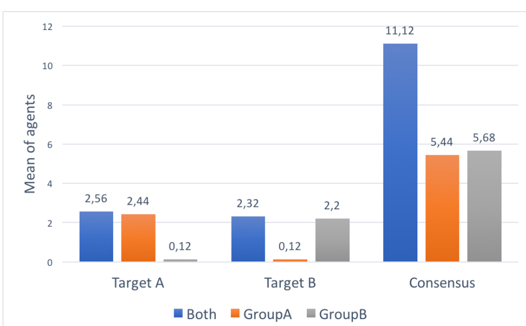
If we compare, the result attained for Environment 1 in the Figure 6.2 to the results of Environment 2 as shown in the Figure 6.6. We can also observed an increase in the mean value of agents at Consensus Target. In Environment 1, the highest mean value was attained at Case 7, where as in Environment 2 Case 8 resulted in higher value. From the results so far, our analysis is that with higher range of communication radius the mean of agents at Consensus target increases given the other parameters are same.



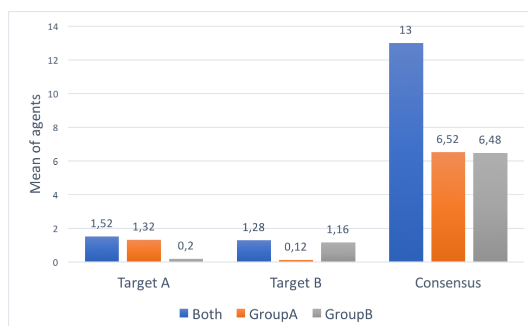
(a) Case 5



(b) Case 6



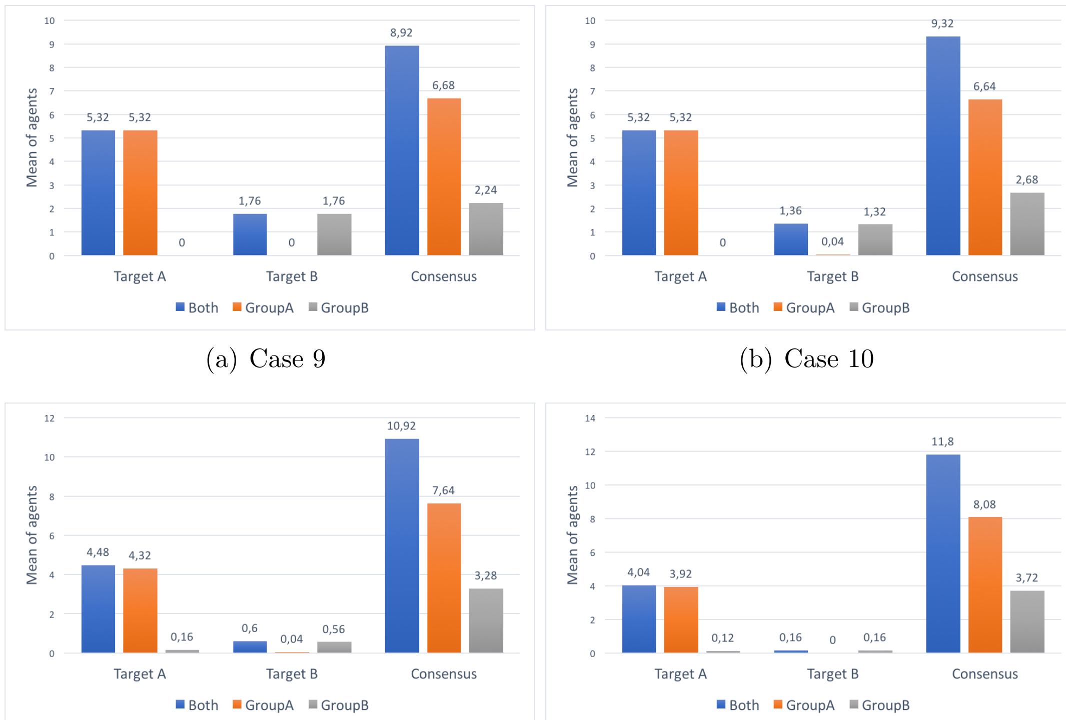
(c) Case 7



(d) Case 8

Figure 6.6: Mixed group with Environment 2; results showing $\bar{x}$ of agents after 25 simulations run for Case 5 to 8 with ratio 8:8. Each case represents a distinctive ratio of how many agents from group type A or B have reached Target A, B and Consensus.

In the Figure 6.7, the plots represents cases from 9 to 12 with ratio of 12:4 of type A and B agents respectively. The results from these plots show the inverse of the results from Figure 6.5 of 4:12 ratio. The mean value at Consensus is greater than 60 % of the total agents with 10.24 value. Likewise, the ratio of agents from *GroupA* is greater than 7.26 on Consensus target, which is certainly because of the reason that more group type A agents are present in the mixed group. In the Case 12, the value of *Both* agents on Consensus has reached 11.8 which is higher than other cases from this ratio. The parameters for Case 12 are $C_r = 0.8$ and FOV $= 270°$, which is similar trend as observed in previous cases and parameter settings.



(a) Case 9 (b) Case 10

(c) Case 11 (d) Case 12

Figure 6.7: Mixed group with Environment 1; results showing $\bar{x}$ of agents after 25 simulations run for Case 9 to 12 with ratio 12:4. Each case represents a distinctive ratio of how many agents from group type A or B have reached Target A, B and Consensus.

To conclude, the overall results of Environment 2 with different parameter settings, we have observed that greater mean values are achieved in the Case 4, 8 and 12 where the $C_r = 0.8$ and FOV $= 270°$. In comparison with Environment 1 analysis, here the parameter settings are same for communication radius and viewing range. Hence, the performance of decision making model to attain higher mean at Consensus is achieved in Environment 2.

On the next page, we have Table 6.5, which shows the SD and SEM for Environment 2 test cases. The Figure 6.8 shows how much the mean is deviating from its value. The red bars show the SEM.

Case no.	**SD** σ	**SEM** $\sigma_{\bar{x}}$ $\pm$
1	3.903	1.951
2	4.205	2.103
3	4.633	2.317
4	4.853	2.427
5	4.091	2.045
6	4.401	2.20
7	4.885	2.443
8	6.027	3.014
9	3.957	1.978
10	4.204	2.102
11	5.023	2.511
12	5.525	2.763

Table 6.5: Mixed group with Environment 2 for all cases values of SD σ and SEM $\sigma_{\bar{x}}$ where sample mean $\bar{x}$=4

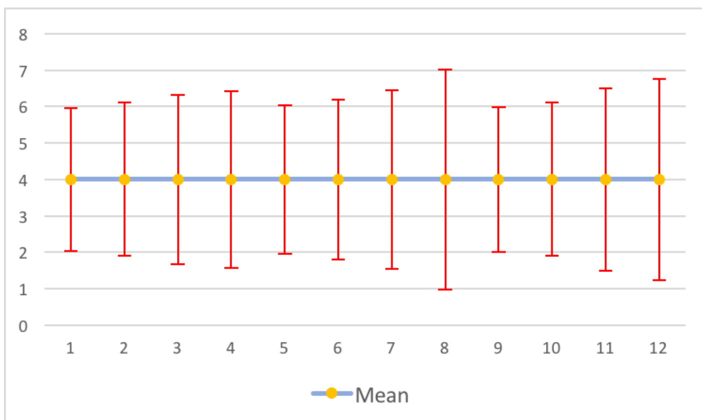


Figure 6.8: Mixed group with Environment 2; all cases SEM with $\bar{x}$ =4

The results at the Consensus Target are the most interesting for our simulation model. The next table shows the data from 4 cases where the ratio of agents is same for both environments. The Table 6.6, shows the total mean of agents on *Env1* and *Env2* for Cases 1 to 4 with ratio 4:12, and the computed sample mean, SD and SEM.

Likewise, for the other two ratios 8:8 and 12:4 the next Table 6.7 and Table 6.8 shows the computed mean, SD and SEM. The data is plotted in Figure 6.9 and Figure 6.10 categorised with Environment 1 and 2 respectively. The plot shows further the distribution of data with respect to each ratio and SEM value, which is represented as a red bar on top of each blue block.

Case no.	**Env1**	**Env2**
1	8.60	8.56
2	8.64	9.24
3	8.72	10.00
4	9.32	10.64
Mean $\bar{x}$, SD σ and SEM $\sigma_{\bar{x}}$	$\bar{x} = 8.82$	$\bar{x} = 9.61$
	$\sigma = 0.209$	$\sigma = 0.533$
	$\sigma_{\bar{x}} = 0.070$	$\sigma_{\bar{x}} = 0.172$

Table 6.6: Consensus Target mean data from Case 1 to 4 for both Environments with ratio 4:12, the table shows the SD and SEM values

Case no.	**Env1**	**Env2**
5	8.60	9.72
6	9.44	10.28
7	9.92	11.12
8	9.72	13.00
Mean $\bar{x}$, SD σ and SEM $\sigma_{\bar{x}}$	$\bar{x} = 9.420$	$\bar{x} = 11.03$
	$\sigma = 0.347$	$\sigma = 0.784$
	$\sigma_{\bar{x}} = 0.113$	$\sigma_{\bar{x}} = 0.236$

Table 6.7: Consensus Target mean data from Case 5 to 8 for both Environments with ratio 8:8, the table shows the SD and SEM values

Case no.	**Env1**	**Env2**
9	8.32	8.92
10	8.60	9.32
11	9.40	10.92
12	9.00	11.80
Mean $\bar{x}$, SD σ and SEM $\sigma_{\bar{x}}$	$\bar{x} = 8.83$	$\bar{x} = 10.24$
	$\sigma = 0.292$	$\sigma = 0.770$
	$\sigma_{\bar{x}} = 0.098$	$\sigma_{\bar{x}} = 0.241$

Table 6.8: Consensus Target mean data from Case 9 to 12 for both Environments with ratio 12:4, the table shows the SD and SEM values

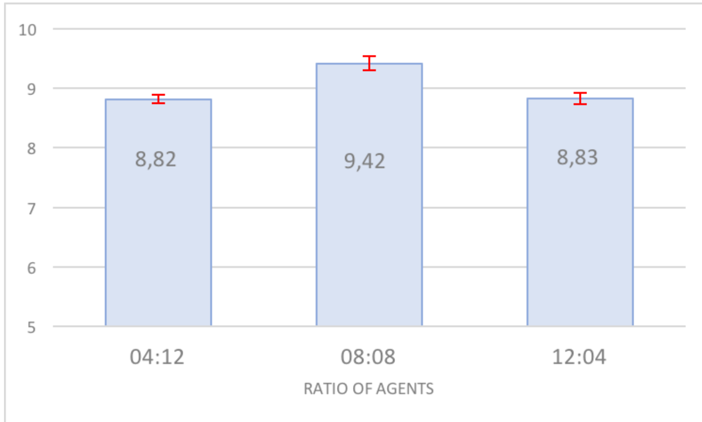


Figure 6.9: Consensus Target with Environment 1; all cases with SEM in red bar.

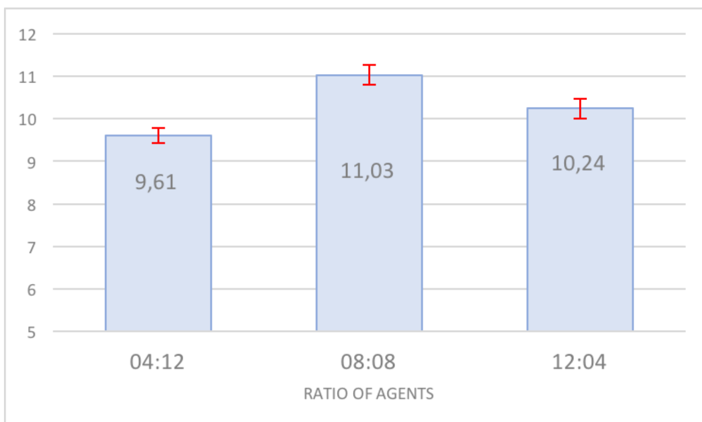


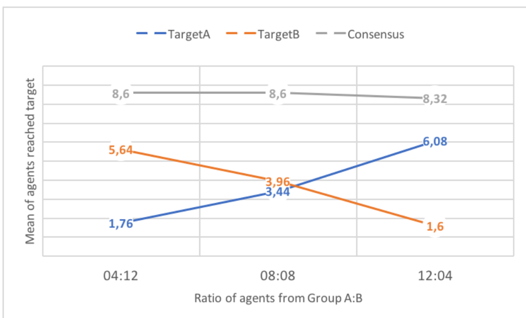
Figure 6.10: Consensus Target with Environment 2; all cases with SEM in red bar.

To summarize, the results from mixed group at Consensus Target. In comparison of the data in Figure 6.9 and Figure 6.10, the mean value on all ratios are higher in Environment 2 cases. Even though, it is not the exact environment settings as MiE approach, but it gave us a comparative scenario to observed behaviour of agents. The results attained in the Environment 1 cases all mean value more than 50% of the total agents, which is still satisfactory result of our simulation model.

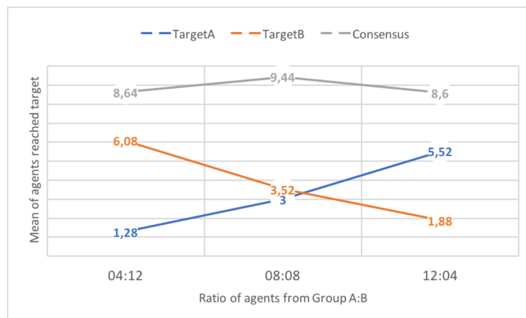
The next part shows the trend plots about, how the different ratios of agents affect the mean value on each Target. The plots are shown in Figure 6.11 and Figure 6.12 and their respective case numbers as caption. The parameter settings for each case is represented in Table 6.2 in the start of this section.

6.2.1.3 Agents Ratio

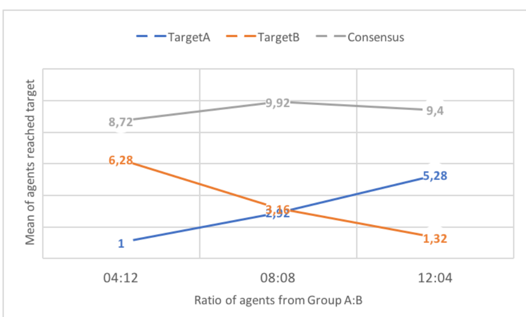
The trend plots shows that the mean value of agents at Consensus target is always higher than the other targets, regardless of the ratio settings Figure 6.11. Each plot in the figure, shows data from three-cases i.e. (a) represents the same parameter settings from Table 6.2 but with different ratio of agents. The results in (a) shows that on Consensus target mean value is 8.6 which is same for 4:12 and 8:8 agents ratio. Where as, in (b), (c) and (d) the Consensus with 8:8 ratio, has reached higher mean value with 9.44, 9.92 and 9.72 respectively.



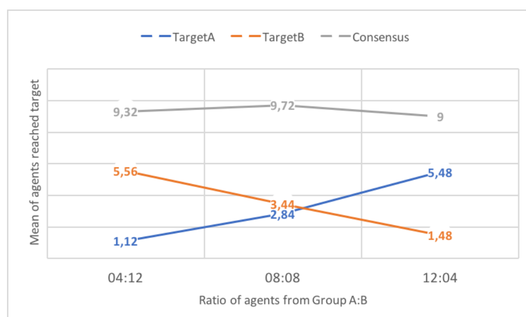
(a) Case 1,5,9



(b) Case 2,6,10



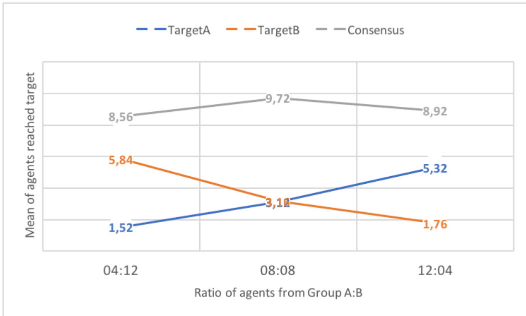
(c) Case 3,7,11



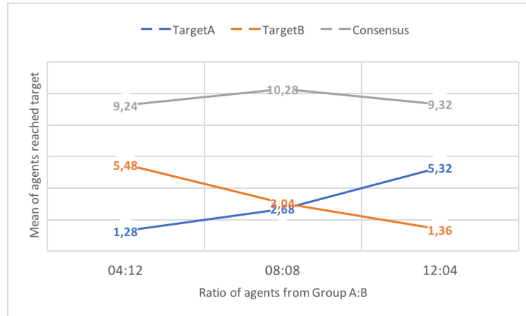
(d) Case 4,8,12

Figure 6.11: Mixed group trend plots with Environment 1, showing how the change in ratio of agents from group type A and B, alter the results for cases.

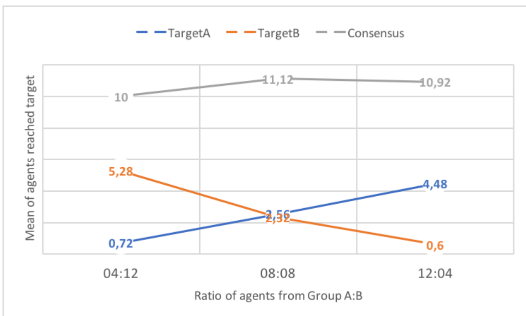
In the Figure 6.12, the trend plots of Environment 2 are shown with the respective ratios and case numbers. The mean value at the Consensus target is higher in all ratios, this is discussed in detail already in previous section. The reason for this increase is because of no wall collision encountered by agents while steering towards target. Hence, the decision making process of an agent is not influenced by any interruption of collision avoidance mechanism. The much higher mean value is reached in (d) with 13.0 value when the ratio of agents is 8:8 (equal in number).



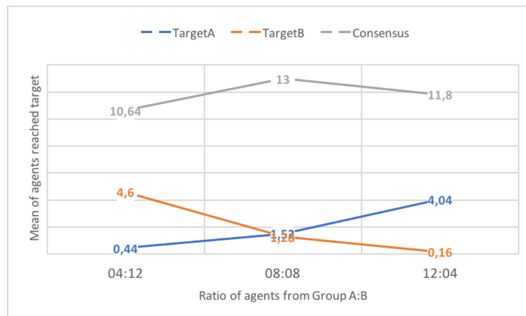
(a) Case 1,5,9



(b) Case 2,6,10



(c) Case 3,7,11



(d) Case 4,8,12

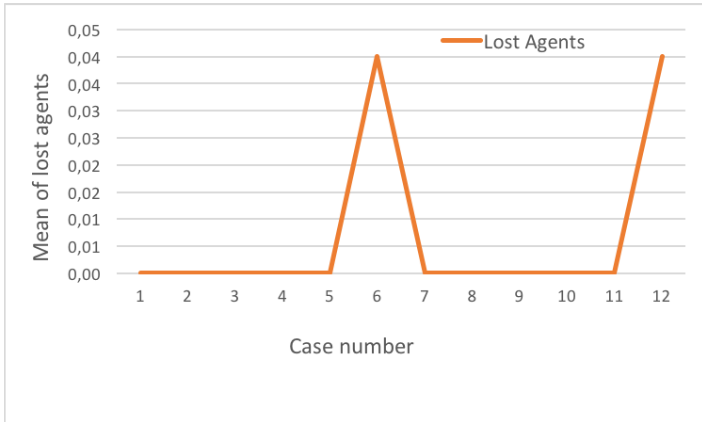
Figure 6.12: Mixed group trend plots with Environment 2, showing how the change in ratio of agents from group type A and B, alter the results for cases.

6.2.1.4 Agents Lost

During the simulation test run, we also noticed at some points there were some agents who couldn't reach their target in time. It is also important to highlight on which cases this has happened under what parameter settings. The only reason of agents being lost is cause of the expiring of simulation time. This also means that this loss of agents can be decreased by increasing the simulation time.

In the Figure 6.13 on next page, the mean of lost agents for all cases from Table 6.2 is shown with respect to both environments. The total mean of lost agents is less than 0.35 and it is evident from 6.13(a) in comparison to 6.13(b), that the mean is less with the Environment 1 setup. It is because of the collision avoidance with walls, that the agents reach targets in a controlled environment. The walls of arena act as a barrier to let agent get back in the right direction to the target. The mechanism of wall avoidance, does not let agent being stuck with it for too long, infact when agent collides with a wall to move beyond it. The new direction for the agent is processed and once agent moves in that direction, in the next time-step it recalculated which is the right direction to take for the known target.

On the other hand, in the scenario of Environment 2; there are no obstacle between agent and the target. Hence, depending on the agent neighbours and their preferred direction, the agent gets an average heading direction. This direction in an open arena is probably not the right heading direction to the defined targets. So, the local flock is lost in finding its target and if the simulation time expires. Those agents are characterized as Lost agents. If the simulation time is increased, the mean value of lost agents can be decreased to almost negligible value or zero.



(a) Environment 1

(b) Environment 2

Figure 6.13: Mixed group: Mean of lost agents for all cases with both environments.

6.2.1.5 Leader-Follower

The decision making of an agent is highly dependent on its neighbours and its position in the local-space of those neighbours. If an agent is a loner and has no neighbours, it has a character of *Leader* and this agent finds its way to the nearest known target based on its only personal-information. On the other hand, if an agent is part of the local flock and has neighbours more than zero. Then it acts like a *Follower* within this local-flock and gets influenced by the neighbours decision and preferences. Hence, these agents rely both on personal and social information. It is also important to analyse that how many times during the simulation run for each case from agent type A and B, were Leader-Follower.

In the start of each simulation run, an agent has *None* character and as soon it crosses the LOC the character is set based on its neighbourhood and position in the local flock. The frequency of character of an agent is calculated over the total travel time until it reaches a target and its character is of Achiever. If the simulation time expires, then the last character assigned to an agent is *Lost*. The total occurrences of *Leader* and *Follower* character are counted and divided by the total character assignment for an agent over time. This gives us, the frequency of how many times a character was *Leader* or *Follower*.

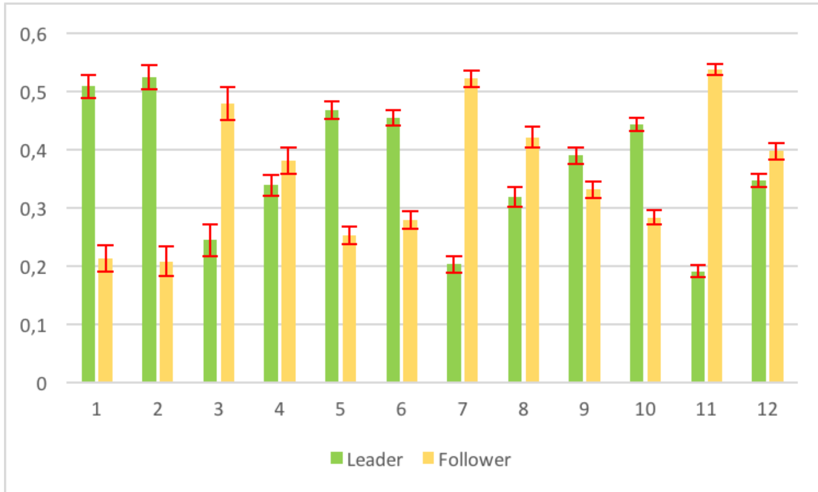
Likewise, for all agents in the simulation the frequency is calculated and at end of each case for 25 simulation run a mean is calculated. The mean of *Leader* and *Follower* is always less than 1, as we are not considering other characters that were assigned during the agent travel time. The Table 6.9 shows the mean of Leader-Follower for group type A agents and the Table 6.10 shows the mean data for agents with type B.

Case no.	**Leader Mean**	**Leader $\sigma_{\bar{x}}$**	**Follower Mean**	**Follower $\sigma_{\bar{x}}$**
1	0.509	0.020	0.213	0.022
2	0.525	0.021	0.208	0.025
3	0.244	0.027	0.479	0.029
4	0.339	0.018	0.381	0.023
5	0.467	0.015	0.253	0.015
6	0.454	0.013	0.279	0.015
7	0.203	0.014	0.522	0.014
8	0.318	0.017	0.421	0.018
9	0.390	0.014	0.331	0.014
10	0.443	0.012	0.283	0.012
11	0.191	0.010	0.538	0.010
12	0.347	0.012	0.397	0.014

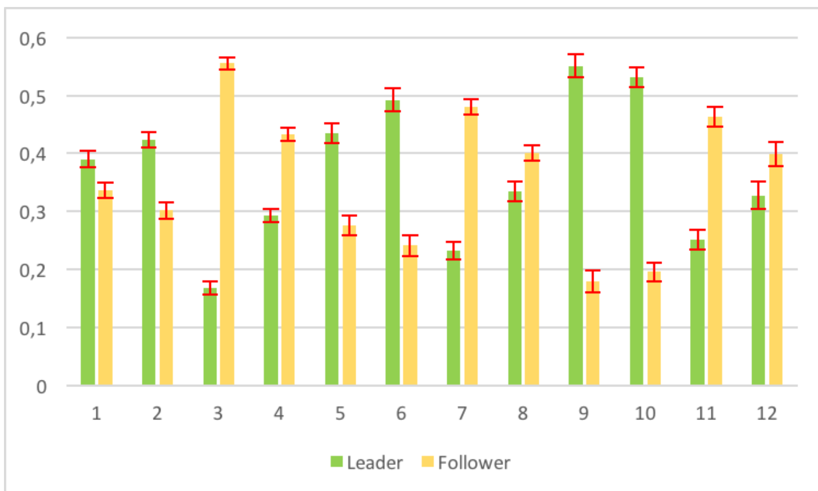
Table 6.9: Mixed group with Environment 1; group type A agents Leader-Follower mean and SEM values from all cases.

Case no.	**Leader Mean**	**Leader $\sigma_{\bar{x}}$**	**Follower Mean**	**Follower $\sigma_{\bar{x}}$**
1	0.390	0.014	0.336	0.013
2	0.423	0.013	0.302	0.014
3	0.169	0.011	0.555	0.010
4	0.293	0.011	0.433	0.011
5	0.435	0.017	0.276	0.017
6	0.492	0.020	0.242	0.018
7	0.232	0.015	0.480	0.013
8	0.335	0.017	0.401	0.013
9	0.551	0.020	0.180	0.019
10	0.531	0.017	0.196	0.016
11	0.252	0.017	0.463	0.017
12	0.328	0.023	0.399	0.020

Table 6.10: Mixed group with Environment 1; group type B agents Leader-Follower mean and SEM values from all cases.



(a) Group type A



(b) Group type B

Figure 6.14: Mixed group - Environment 1; Leader-Follower mean with SEM.

In the Figure 6.14, the mean of Leader and Follower character is shown with the SEM in the red bar, the values of the plot are from the respective table data of groups Table 6.9 for type A agents and Table 6.10 for type B agents.

Likewise, for all agents in the simulation the frequency is calculated and at end of each case for 25 simulation run a mean is calculated. The mean of Leader and Follower is always less than 1, as we are not considering other characters that were taken during the simulation.

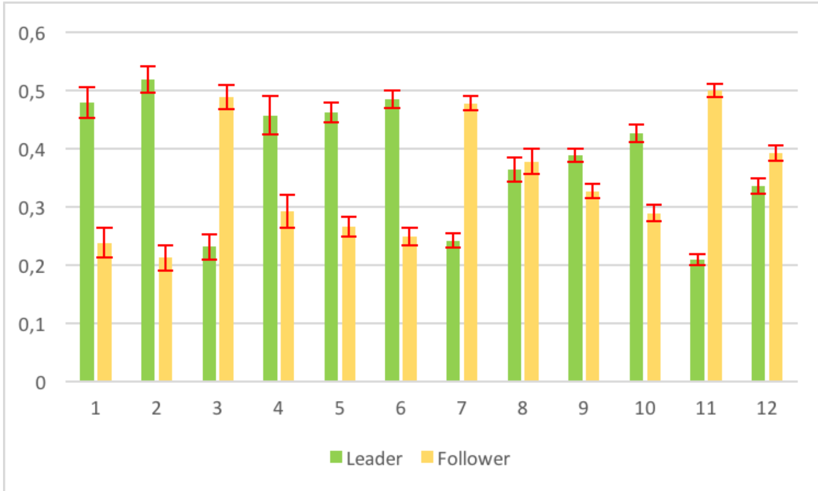
Case no.	Leader Mean	Leader $\sigma_{\bar{x}}$	Follower Mean	Follower $\sigma_{\bar{x}}$
1	0.479	0.026	0.238	0.025
2	0.519	0.022	0.212	0.021
3	0.231	0.022	0.488	0.021
4	0.457	0.033	0.292	0.028
5	0.463	0.017	0.266	0.017
6	0.485	0.015	0.248	0.015
7	0.242	0.012	0.478	0.012
8	0.364	0.020	0.378	0.021
9	0.389	0.011	0.327	0.013
10	0.427	0.015	0.289	0.014
11	0.209	0.010	0.50	0.011
12	0.335	0.013	0.392	0.013

Table 6.11: Mixed group with Environment 2; group type A agents Leader-Follower mean and SEM values from all cases.

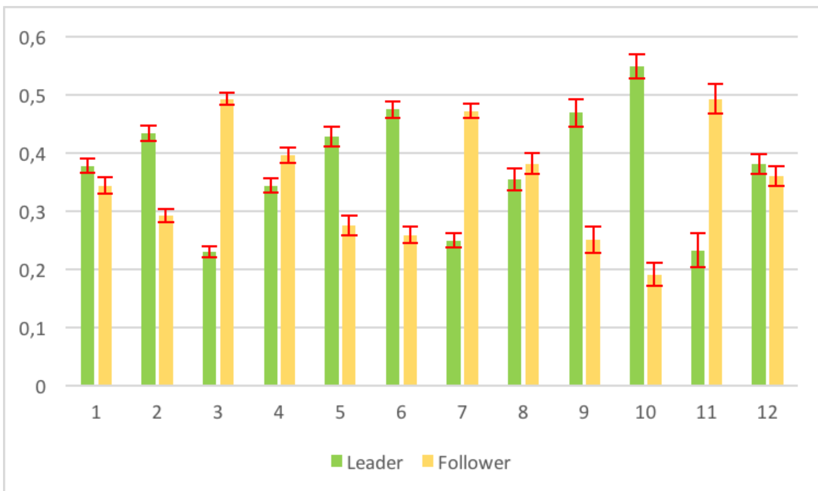
Case no.	Leader Mean	Leader $\sigma_{\bar{x}}$	Follower Mean	Follower $\sigma_{\bar{x}}$
1	0.378	0.013	0.344	0.014
2	0.434	0.013	0.292	0.012
3	0.230	0.010	0.493	0.010
4	0.344	0.012	0.396	0.013
5	0.429	0.017	0.276	0.017
6	0.475	0.014	0.259	0.015
7	0.249	0.012	0.472	0.012
8	0.355	0.019	0.381	0.018
9	0.469	0.023	0.251	0.023
10	0.549	0.020	0.191	0.019
11	0.232	0.029	0.493	0.026
12	0.380	0.017	0.361	0.017

Table 6.12: Mixed group with Environment 2; group type B agents Leader-Follower mean and SEM values from all cases.

Likewise, for the Environment 2; the data from the Table 6.11 and Table 6.12 is used in plots Figure 6.15 to show mean of Leader-Follower for group type A and B agents. There is no clear pattern of how many times an agent is Leader on specific cases, because the character evolves based on the start position of an agent in the Start Arm. The spawning of agents into the Start Arm is based on uniform-random distribution. The agent who is near to LOC in the iteration 1 of simulation, in next iteration might get a random position of being last in the start region. The position of an agent also affects the neighbours he would have during the simulation time. Hence, the characters of an agent are highly affected based on its position and neighbours in that time-step.



(a) Group type A



(b) Group type B

Figure 6.15: Mixed group - Environment 2; Leader-Follower mean with SEM.

6.2.2 Unmixed group

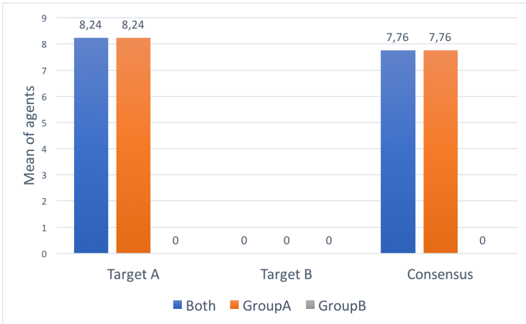
The second experiment we did is on the unmixed group, where the agents are only from one trained group at a time in the arena. In the Table 6.13, all the test cases for the unmixed group are given with their specific values. The agents total count is set to 16 for unmixed group and again these cases are tested with both environments. In Figure 6.16, the 8 cases for agents with primary target as A are represented. Where Case 1 to 4 are with Environment 1 setup and Case 5 to 8 are with Environment 2. In each simulation run, the 16 agents from group type A are selected for the test. The results show approximately an equal mean on Target A and Consensus,it is because the agent has pre-defined memory of both targets. Please note, that both targets have equal weight, which means at time of decision making which ever is near to the target will be preferred. On Target B, there are no agents, this is of-course for a reason that agents have no memory of this target. The similar representation for group type B agents is shown in Figure 6.17. The results show similar pattern of result, as we have just seen for group type A agent. For B type agents as well, approximately an equal mean on Target B and Consensus can be seen. There is more difference in mean values for Case 4,5,6 and 8, this could be because of the randomised start position of the agents in the Start region.

Case no.	**Env**	C_r	**FOV**
1	1	0.4	180°
2	1	0.4	270°
3	1	0.8	180°
4	1	0.8	270°
5	2	0.4	180°
6	2	0.4	270°
7	2	0.8	180°
8	2	0.8	270°

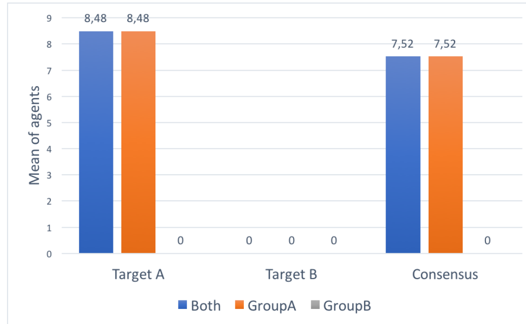
Table 6.13: Unmixed group with all possible cases based on parameter settings, Env, C_r and FOV. These cases are evaluated for both group type agents A and B

The results from unmixed does not show much difference with the variations of parameter settings. Hence, they are not evaluated further for any trends or Leader-Follower frequency. In unmixed group, an approximately equal mean value was obtained on both pre-defined targets, with no loss of agents during any simulation. This is because of the fact, that each agent in the group had same pre-defined targets and was not influenced by any other conflicting opinion.

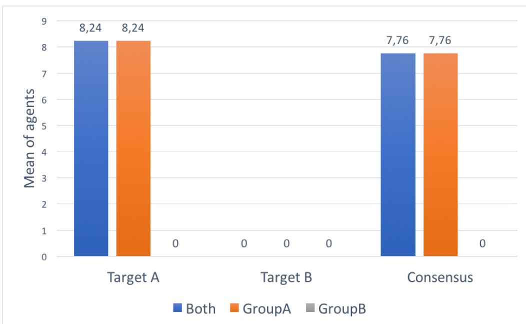
To conclude our evaluation with an overall summary of results from both experiments, it is worth mentioning that our simulation model results has generated satisfactory results in mixed group by achieving more than 50% mean value at Consensus target, with all the cases from either Environment 1 or 2. The ratio of agents reaching consensus also shows, how the decision of an individual is influenced because of its neighbouring agents. In some cases,the mean value even raised to 65% of total agents reaching at Consensus Target, specially in the cases where ratio is of 8:8 agents.



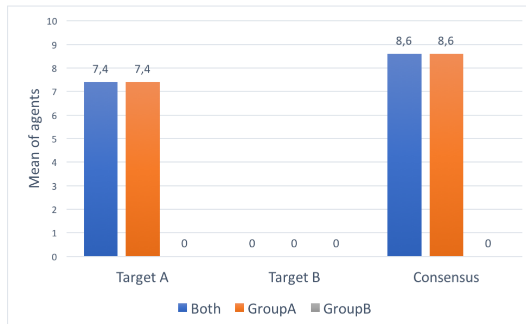
(Case 1)



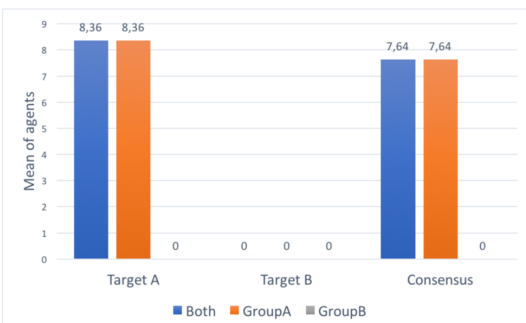
(Case 2)



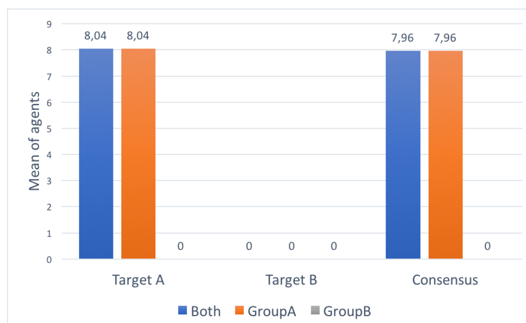
(Case 3)



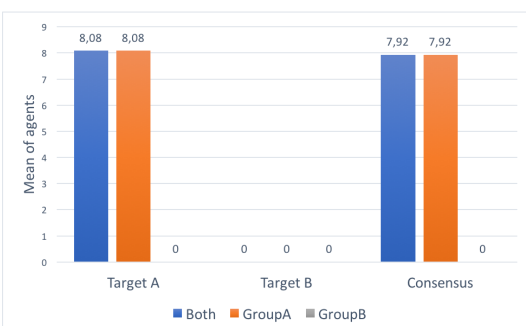
(Case 4)



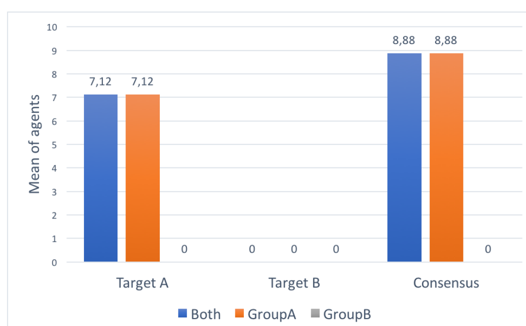
(Case 5)



(Case 6)

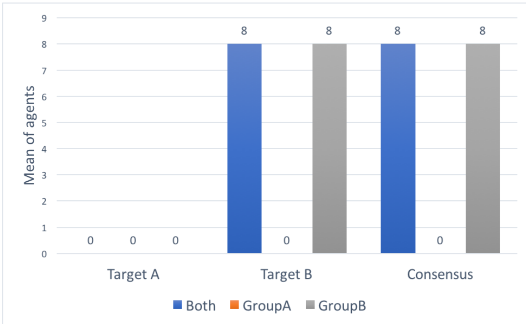


(Case 7)



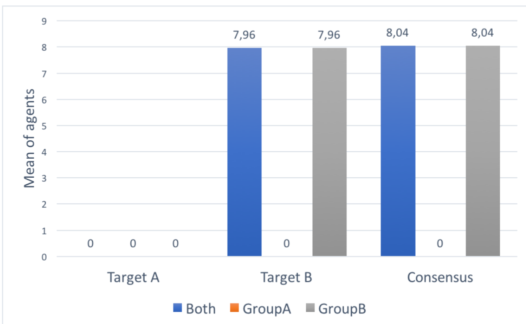
(Case 8)

Figure 6.16: Unmixed group for agent type A, showing mean of agents after 25 simulations run. Each case represents a distinctive ratio of how many agents from group B have reached a Target A, B and Consensus.



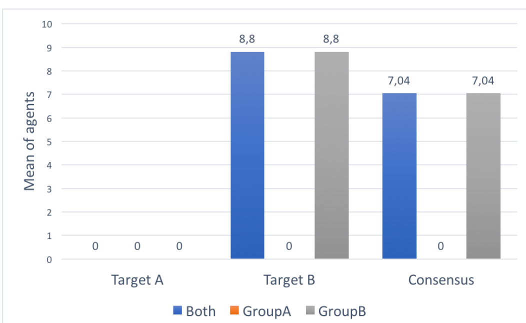
(Case 1)

(Case 2)

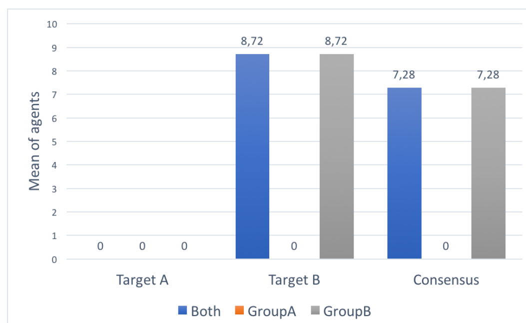


(Case 3)

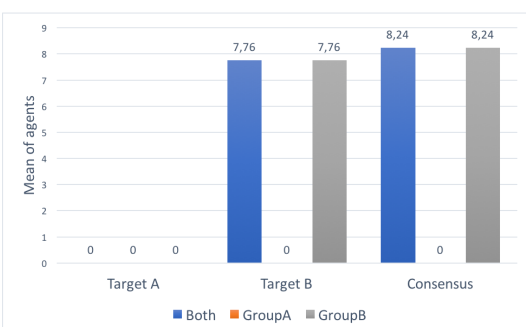
(Case 4)



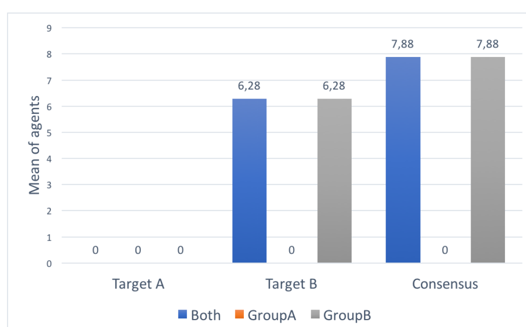
(Case 5)



(Case 6)



(Case 7)



(Case 8)

Figure 6.17: Unmixed group for agents type B, showing mean of agents after 25 simulations run. Each case represents a distinctive ratio of how many agents from group B have reached a Target A, B and Consensus.

7. Conclusion

In this thesis, we have proposed a self-organized collective decision making approach, to achieve consensus in a multi-target environment, with multi-agent systems. For our model, we developed a simulation with fish school, in which each agent is represented as an independent individual, who can take decisions based on its personal and social information. The experiment conducted in the simulation was based on a MiE biological experiment [38]. The results we obtained from the simulation as compared to the biological experiment seems to be promising and mean proportion of agents at Consensus target reached more than 50% of the total agents in the mixed group experiment of our simulation. Although, there is not a possibility of 1-1 comparison of the results from MiE to our simulation model, because the biological experiment involved real golden shiner fish with visual cues to exchange information within neighbourhood. In our simulation model on the other side, we used a fixed position in a space as seeking target. The target is pre-defined in the agent's brain as memory and there is no learning involved during the simulation about the spatial aspect of an agent visiting a site before. Every agent has a defined target to achieve in two set of environments over a course of time.

From our simulation model all the test cases, resulted in mean value of more than 50% of the agents who reached Consensus target. In the decision making model, we have used voter model approach to rate every direction of an agent based on its minimum distance to the known targets. This approach has proven to work for both experiments on mixed group (A and B type agents) and unmixed group (A or B type agents). Also, the results have shown that the change in parameter values of the simulation are increasing and decreasing the mean value of agents at Consensus target. The most important parameter in the multi-agent systems is of the Communication Radius C_r, the higher the value of the radius, the more neighbours decisions are taken into consideration and hence it improves the decision making process. The other important parameter is of the FOV which helps in refining the agents in the neighbourhood, as our simulated agent represents a fish. It is important to eliminate the neighbour on the tail side. Hence, the wide viewing range of FOV also gives higher mean than the narrow field at Consensus target.

We also did experiment with two different environments, which showed varied results on the Consensus target. The collision avoidance in the Environment 1, misleads the agent from its target when the collision mechanism is applied. Once reaching to this new direction, the agent predicts again the next direction to take to find the nearest target. On the other hand, the collision avoidance also helps agent to reach the target if their local flock has computed an average direction which is not leading towards any target. But once an agent collides with a wall, due to the iterative decision making process it computes again the right direction to its target, which does not happen in the Environment 2 setting.

In Environment 2, the results on Consensus target reached up to 65% of mean. This is because of no walls and obstacles in between an agent and the target to seek. The agents which are randomly spawn near to the LOC are most likely to decide for their target sooner than the other agents and hence reach straight towards their preferred target with no interruption in between. But this also, sometimes lead to the issue of lost agent, because of the average heading of local flock leading to a direction which is not within the radius of target. Until, an external factor re-computes the average heading of a local flock, the agents roam around in a average heading direction based on the neighbourhood preference.

The proposed model and simulation shows that it can be used in different form of applications to understand fish schooling or swarm intelligence behaviour in general. The collective decision making within a swarm is a challenging task, but we hope that the proposed model will be helpful in taking a step in the right direction to achieve consensus in multi-agent systems. The common applications, where this proposed model could be helpful is of swarm intelligence educational purpose, swarm robotics, simulation games and video games.

In the scope of this thesis work, the proposed model is tested and analysed only for agent achieving Consensus. We believe that the model can be improved and expanded with more possibilities; it can also be tested with more multi-target and different environment settings and also dynamic target seeking behaviour where target position is changing over time. The collision avoidance mechanism implemented in the model can also be improved by selecting the next best direction which gives the minimum distance to a target, instead of taking inverse direction. We believe that, taking inverse direction does halt the decision making process of an agent and hence it can get deviated from the preferred target. The targets are static throughout the simulation duration and hence the dynamic seeking behaviour of a swarm is not possible at the current state of proposed model, but it can be easily modified to attain the updated position of targets moving in the arena. The updated target position can be stored as an input in agent's brain, for re-computing which direction to take based on new target position.

The limitation of the current model is that there is no spatial memory or image processing technique used to learn the targets over time. Due to this limitation, the targets information is stored in agent's brain in the form of global position. Hence, the results in the unmixed group are not the real depiction of consensus as the agents steer towards their pre-defined targets which are already stored in their memory. Although, in the mixed group due to the conflicting preferences of the agents the higher range of agents of both types reach the Consensus target. This can be further tested, with the pre-defined target information having different weights, i.e the primary target has higher weight and the secondary target with lower weights.

In the future work, we can propose that the presented model can be extended and tested for 3D movement of swarm. The model can also be implemented and tested on swarm robotics, where the robots are trained with pre-defined targets and are tested later to check, if they can achieve consensus over time. We have seen in the unmixed group testing, that the agents reached their preferred target while keeping cohesion and alignment with local flock. So, the proposed model can also be compared with the BOIDS algorithm with seeking target behaviour to test the performance of the proposed model. Additionally, the proposed model can be optimised for the dynamic seeking behaviour of agents in an arena with multiple targets from different trained groups.

We hope that thesis can be used for academic and application purpose. There is definitely, a broader scope to the presented problem and more robust and optimised solutions are possible for collective decision making in swarm.

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List of Algorithms

List of Acronyms

AI	Artificial intelligence
CDM	Collective decision-making
FOV	Field of view
LOC	Line of control
MAS	Multi-agent system
MCDM	Multi-criteria decision-making
MiE	Miller's Experiment
MOP	Multi-objective problem
NII	Nature inspired intelligent
SD	Standard deviation
SEM	Standard error mean
SI	Swarm intelligence
SOB	Self-organised behaviour
UI	User interface
WSM	Weighted sum model
WVM	Weighted-voter model

Bibliography

[1] Abaid, N. and Porfiri, M. (2010). Collective behavior of fish shoals in one-dimensional annular domains. In *American Control Conference (ACC), 2010*, pages 63–68. IEEE. (cited on Page 19) 119

[2] Abd-Alsabour, N. (2017). Nature as a source for inspiring new optimization algorithms. In *Proceedings of the 9th International Conference on Signal Processing Systems*, pages 51–56. ACM. (cited on Page 9) 19

[3] A.David, M. (2018). Behaviour patterns. http://www.biologyreference.com/Ar-Bi/Behavior-Patterns.html. Last accessed 10 Febuary 2018. (cited on Page 4) 14

[4] Alcock, J. (2003). A textbook history of animal behaviour. (cited on Page 3) 13

[5] Aoki, I. (1982). A Simulation Study on the Schooling Mechanism in Fish. *Bulletin of the Japanese Society of Scientific Fisheries*, 48(8):1081–1088. (cited on Page 1 and 18) 21 and 18

[6] Ballerini, M., Cabibbo, N., Candelier, R., Cavagna, A., Cisbani, E., Giardina, I., Lecomte, V., Orlandi, A., Parisi, G., Procaccini, A., et al. (2008). Interaction ruling animal collective behavior depends on topological rather than metric distance: Evidence from a field study. *Proceedings of the national academy of sciences*, 105(4):1232–1237. (cited on Page 19 and 20) 219 and 20

[7] Barde, M. and Barde, P. (2012). What to use to express the variability of data: Standard deviation or standard error of mean? *Perspectives in Clinical Research*, 3(3):113–116. (cited on Page 56) 156

[8] Ben-Arieh, D. and Chen, Z. (2006). Linguistic-labels aggregation and consensus measure for autocratic decision making using group recommendations. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 36(3):558–568. (cited on Page 9) 19

[9] Blum, C. (2005). Ant colony optimization: Introduction and recent trends. *Physics of Life reviews*, 2(4):353–373. (cited on Page 12 and 18) 212 and 18

[10] Bonabeau, E., Corne, D., and Poli, R. (2010). Swarm intelligence: the state of the art special issue of natural computing. *Natural Computing*, 9(3):655–657. (cited on Page 11) 111

[11] Bonabeau, E., Dorigo, M., and Theraulaz, G. (1999). *Swarm intelligence: from natural to artificial systems*. Number 1. Oxford university press. (cited on Page 11 and 18) 211 and 18

[12] Brambilla, M., Ferrante, E., Birattari, M., and Dorigo, M. (2013). Swarm robotics: a review from the swarm engineering perspective. *Swarm Intelligence*, 7(1):1–41. (cited on Page 13, 14, 18, and ix) 413, 14, 18, and ix

[13] Brans, J.-P. and Vincke, P. (1985). Note—a preference ranking organisation method: (the promethee method for multiple criteria decision-making). *Management science*, 31(6):647–656. (cited on Page 9) 19

[14] Camazine, S., Deneubourg, J., Franks, N., Sneyd, J., Theraulaz, G., and Bonabeau, E. (2001). Self-organization in biological systems. *Princeton, NJ: Princeton University Press*. (cited on Page 14 and 17) 214 and 17

[15] Conradt, L. and Roper, T. J. (2005). Consensus decision making in animals. *Trends in ecology & evolution*, 20(8):449–456. (cited on Page 18) 218 and 18

[16] Couzin, I. (2007). Collective minds. *Nature*, 445(7129):715. (cited on Page 17) 117

[17] Couzin, I. D. (2009). Collective cognition in animal groups. *Trends in Cognitive Sciences*, 13(1):36–43. (cited on Page 3 and 18) 23 and 18

[18] Couzin, I. D., Ioannou, C. C., Demirel, G., Gross, T., Torney, C. J., Hartnett, A., Conradt, L., Levin, S. A., and Leonard, N. E. (2011). Uninformed individuals promote democratic consensus in animal groups. *science*, 334(6062):1578–1580. (cited on Page 19) 119

[19] Couzin, I. D. and Krause, J. (2003). Self-organization and collective behavior in vertebrates. (cited on Page 17 and 18) 217 and 18

[20] Couzin, I. D., Krause, J., Franks, N. R., and Levin, S. A. (2005). Effective leadership and decision-making in animal groups on the move. *Nature*, 433(7025):513. (cited on Page 19) 119

[21] Couzin, I. D., Krause, J., James, R., Ruxton, G. D., and Franks, N. R. (2002a). Collective memory and spatial sorting in animal groups. *Journal of Theoretical Biology*. (cited on Page 1, 12, and 17) 31, 12, and 17

[22] Couzin, I. D., Krause, J., James, R., Ruxton, G. D., and Franks, N. R. (2002b). Collective memory and spatial sorting in animal groups. *Journal of theoretical biology*, 218(1):1–11. (cited on Page 18, 19, and ix) 318, 19, and ix

[23] Franks, N. R., Pratt, S. C., Mallon, E. B., Britton, N. F., and Sumpter, D. J. (2002). Information flow, opinion polling and collective intelligence in house–hunting social insects. *Philosophical Transactions of the Royal Society of London B: Biological Sciences*, 357(1427):1567–1583. (cited on Page 18) 118

[24] Goller, F. and Esch, H. (1990). Waggle dances of honey bees. *Naturwissenschaften*, 77(12):594–595. (cited on Page 18) 118

[25] Herrera, F., Herrera-Viedma, E., et al. (1996). A model of consensus in group decision making under linguistic assessments. *Fuzzy sets and Systems*, 78(1):73–87. (cited on Page 9) 19

[26] Herrera-Viedma, E., Martinez, L., Mata, F., and Chiclana, F. (2005). A consensus support system model for group decision-making problems with multigranular linguistic preference relations. *IEEE Transactions on fuzzy Systems*, 13(5):644–658. (cited on Page 12) 112

[27] Huth, A. and Wissel, C. (1992). The simulation of the movement of fish schools. *Journal of theoretical biology*, 156(3):365–385. (cited on Page 18) 118

[28] Jennings, N. R., Sycara, K., and Wooldridge, M. (1998). A roadmap of agent research and development. *Autonomous agents and multi-agent systems*, 1(1):7–38. (cited on Page 9 and 10) 29 and 10

[29] Kennedy, J. (2011). Particle swarm optimization. In *Encyclopedia of machine learning*, pages 760–766. Springer. (cited on Page 12 and 18) 212 and 18

[30] Kitano, H., Asada, M., Kuniyoshi, Y., Noda, I., Osawai, E., and Matsubara, H. (1997). Robocup: A challenge problem for ai and robotics. In *Robot Soccer World Cup*, pages 1–19. Springer. (cited on Page 14 and 18) 214 and 18

[31] Kolpas, A., Busch, M., Li, H., Couzin, I. D., Petzold, L., and Moehlis, J. (2013). How the spatial position of individuals affects their influence on swarms: a numerical comparison of two popular swarm dynamics models. *PloS one*, 8(3):e58525. (cited on Page 19, 20, and ix) 519, 19, 20, 20, and ix

[32] Kumar, A., Sah, B., Singh, A. R., Deng, Y., He, X., Kumar, P., and Bansal, R. (2017). A review of multi criteria decision making (mcdm) towards sustainable renewable energy development. *Renewable and Sustainable Energy Reviews*, 69:596–609. (cited on Page 9) 19

[33] Liu, F.-H. F. and Hai, H. L. (2005). The voting analytic hierarchy process method for selecting supplier. *International journal of production economics*, 97(3):308–317. (cited on Page 9 and 12) 29 and 12

[34] Lopez, U., Gautrais, J., Couzin, I. D., and Theraulaz, G. (2012). From behavioural analyses to models of collective motion in fish schools. *Interface focus*, 2(6):693–707. (cited on Page 18 and 19) 418, 18, 19, and 19

[35] MathOpenReference (2018). Parametric equation. https://www.mathopenref.com/coordparamcircle.html. Last accessed 09 Febuary 2018. (cited on Page 28) 128

[36] Mench, J. (1998). Why it is important to understand animal behavior. *ILAR Journal*, 39(1):20–26. (cited on Page 3) 13

[37] Metkiff, C., Dixon, C., Knieriem, D., and Maurer, R. (2006). Animal Behavior in a Swarm. pages 1–13. (cited on Page 3) 13

[38] Miller, N., Garnier, S., Hartnett, A. T., and Couzin, I. D. (2013). Both information and social cohesion determine collective decisions in animal groups. *Proceedings of the National Academy of Sciences*, 110(13):5263–5268. (cited on Page 1, 6, 12, 14, 15, 17, 21, 22, 75, and ix) 101, 6, 12, 14, 15, 17, 21, 22, 75, and ix

[39] Muralidharan, C., Anantharaman, N., and Deshmukh, S. (2002). A multi-criteria group decisionmaking model for supplier rating. *Journal of supply chain management*, 38(3):22–33. (cited on Page 9) 19

[40] Oboshi, T., Kato, S., Mutoh, A., and Itoh, H. (2003). A simulation study on the form of fish schooling for escape from predator. *FORMA-TOKYO-*, 18(2):119–131. (cited on Page 18) 218 and 18

[41] Okubo, A. (1986a). Dynamical aspects of animal grouping: Swarms, schools, flocks, and herds. *Advances in Biophysics*, 22(C):1–94. (cited on Page 3) 13

[42] Okubo, A. (1986b). Dynamical aspects of animal grouping: swarms, schools, flocks, and herds. *Advances in biophysics*, 22:1–94. (cited on Page 18) 118

[43] Pita, D., Moore, B. A., Tyrrell, L. P., and Fernández-Juricic, E. (2015). Vision in two cyprinid fish: implications for collective behavior. *PeerJ*, 3:e1113. (cited on Page 17 and ix) 317, 17, and ix

[44] Pitcher, T. J. and Partridge, B. L. (1979). Fish school density and volume. *Marine Biology*. (cited on Page 4) 14

[45] Reynolds, C. W. (1987). Flocks, herds and schools: A distributed behavioral model. *ACM SIGGRAPH Computer Graphics*, 21(4):25–34. (cited on Page 1, 6, 14, 18, 44, and ix) 91, 6, 6, 14, 18, 18, 18, 44, and ix

[46] Reynolds, C. W. (1999). Steering behaviors for autonomous characters. In *Game developers conference*, volume 1999, pages 763–782. (cited on Page 18) 118

[47] Russell, S. J. and Norvig, P. (2016). *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited,. (cited on Page 9, 10, and ix) 49, 10, 10, and ix

[48] Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International journal of services sciences*, 1(1):83–98. (cited on Page 13) 113

[49] Seeley, T. D. (2003). Consensus building during nest-site selection in honey bee swarms: the expiration of dissent. *Behavioral Ecology and Sociobiology*, 53(6):417–424. (cited on Page 18) 118

[50] Serugendo, G. D. M., Gleizes, M.-P., and Karageorgos, A. (2005). Self-organization in multi-agent systems. *The Knowledge Engineering Review*, 20(2):165–189. (cited on Page 5, 10, and 11) 45, 10, 10, and 11

[51] Shang, Y. and Bouffanais, R. (2014). Influence of the number of topologically interacting neighbors on swarm dynamics. *Scientific reports*, 4:4184. (cited on Page 14) 114

[52] Shaw, E. (1978). Schooling fishes. *American Scientist*, 66(2):166–175. (cited on Page 1) 11

[53] Siddique, N. and Adeli, H. (2015). Nature inspired computing: an overview and some future directions. *Cognitive computation*, 7(6):706–714. (cited on Page 9) 19

[54] Strandburg-Peshkin, A., Twomey, C. R., Bode, N. W., Kao, A. B., Katz, Y., Ioannou, C. C., Rosenthal, S. B., Torney, C. J., Wu, H. S., Levin, S. A., et al. (2013). Visual sensory networks and effective information transfer in animal groups. *Current Biology*, 23(17):R709–R711. (cited on Page 17) 217 and 17

[55] Sumpter, D. J., Krause, J., James, R., Couzin, I. D., and Ward, A. J. (2008). Consensus decision making by fish. *Current Biology*, 18(22):1773–1777. (cited on Page 18) 218 and 18

[56] Sumpter, D. J. T. (2006). The principles of collective animal behaviour. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 361(1465):5–22. (cited on Page 3) 13

[57] Swartzman, G. (1991). Fish school formation and maintenance: a random encounter model. *Ecological Modelling*. (cited on Page 1 and 5) 21 and 5

[58] Triantaphyllou, E. (2000). Multi-criteria decision making methods. In *Multi-criteria decision making methods: A comparative study*, pages 5–21. Springer. (cited on Page 9 and 13) 39, 13, and 13

[59] Tunstrøm, K., Katz, Y., Ioannou, C. C., Huepe, C., Lutz, M. J., and Couzin, I. D. (2013). Collective States, Multistability and Transitional Behavior in Schooling Fish. *PLoS Computational Biology*, 9(2). (cited on Page 1) 11

[60] Valentini, G. and Dorigo, M. (2015). Self-Organized Collective Decision-Making in a 100-Robot Swarm. *Proceedings of the 29th Conference on Artificial Intelligence (AAAI 2015)*, pages 4216–4217. (cited on Page 14, 16, and 32) 314, 16, and 32

[61] Valentini, G., Ferrante, E., and Dorigo, M. (2017). The Best-of-n Problem in Robot Swarms: Formalization, State of the Art, and Novel Perspectives. *Frontiers in Robotics and AI*, 4(March). (cited on Page 1, 5, 13, 14, 32, and ix) 61, 5, 13, 14, 32, and ix

[62] Valentini, G., Hamann, H., and Dorigo, M. (2014). Self-organized collective decision making: The weighted voter model. *Proceedings of the 13th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2014)*, (Aamas):45–52. (cited on Page 1, 7, 14, 16, and 32) 51, 7, 14, 16, and 32

[63] Vassiliadis, V. and Dounias, G. (2009). Nature–inspired intelligence: A review of selected methods and applications. *International Journal on Artificial Intelligence Tools*, 18(04):487–516. (cited on Page 9) 19

[64] Vincke, P. (1976). A new approach to multiple criteria decision-making. In *Multiple Criteria Decision Making*, pages 341–350. Springer. (cited on Page 9) 19

[65] Weistroffer, H. R., Smith, C. H., and Narula, S. C. (2005). Multiple criteria decision support software. In *Multiple criteria decision analysis: state of the art surveys*, pages 989–1009. Springer. (cited on Page 9) 19

[66] Wibowo, S. and Deng, H. (2013). Consensus-based decision support for multicriteria group decision making. *Computers & Industrial Engineering*, 66(4):625–633. (cited on Page 9 and 12) 29 and 12

[67] Wooldridge, M. and Jennings, N. R. (1995). Intelligent agents: Theory and practice. *The knowledge engineering review*, 10(2):115–152. (cited on Page 9 and 10) 29 and 10

Statement of Declaration

I assure that this research work is done completely by me and no other than the indicated aids have been used for its completion. Furthermore I assure that all quotations and statements that have been inferred literally or in a general manner from published or unpublished writings are marked as such. Beyond this I assure that the work has not been used, neither completely nor in parts, to pass any previous examination.

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May 8, 2018