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Utvikling av altruisme med gjenkjennelse av slektskap i evolusjonære roboter

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Evolving Altruism through Kin Recognition and Kin Selection in Evolutionary Robotics

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Abstract

Swarm robotics provides ways of solving problems using groups of autonomous robots that display emergent intelligent behaviour. Control mechanisms for these robots can be designed by using mechanisms from evolutionary robotics. In order to ensure that the controllers are adaptive and capable of learning new behaviour controllers are artificially evolved using techniques inspired by natural evolution. Altruism can be helpful to ensure that the controllers solve problems in a way that maximizes the utility of the population as a whole. Kin-selection and kin-recognition have been shown to be beneficial for evolving altruism in nature. This report investigates if kin-selection and kin-recognition can be used to ensure the evolution of altruism in evolutionary robotics. An experiment is conducted by giving swarm robots controllers evolved with a genetic algorithm. The robots are given the ability to relinquish fitness and different mechanisms for discerning kin. The results give support to the hypothesis that kin recognition can be used to evolve altruism in evolutionary robotics

Preface

This report was written as a master's thesis in the spring of 2014 at the Norwegian University of Science and Technology. It was officially supervised by Pauline Haddow with co-supervision by Jean-Marc Montanier.

Andreas Hagen
Trondheim, June 18, 2014

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Chapter 1

Introduction

Swarm robotics is an approach to coordinating groups of robots where each single robot is relatively simple. Within this approach advanced behaviour emerges as a result of the collective effort of the robots and their interactions with the environment. This approach is inspired by social insects such as ants and bees and has many advantages:

- The simplicity of construction of each robot make them easy and cost effective to manufacture
- The system is robust with regards to failure of a single robot.
- There is potentially a high level of parallel processing

There are many applications where a problem is best solved by a large number of robots working in unison in large scale multi-agent systems. Şahin [2005] identifies for instance what he calls "tasks that cover a region" such as robots monitoring chemical leaks in a factory. In scenarios like this the robots are situated in an open, uncharted and potentially unstable environment that may change over time. The robots monitoring chemical leaks may have to start monitoring a newly constructed wing of the building complex they are in that has a significantly different layout. The goal then is to design the robots in such a way that they are able to adapt to this new problem. This can be done by continuously changing the control mechanism without interference from the designers. For this goal to be reached the robots need to be able to learn new skills. Evolutionary robotics provides one way of equipping the robots with this ability through techniques inspired by natural evolution.

In natural evolution the traits that are advantageous to a species remain and improve while the traits that are of no use or disadvantageous are lost.

This happens through genetic mutation and cross breeding of genes that are successful in the current environment. Evolutionary robotics uses mechanisms inspired by this process to evolve a population of candidate controllers for the robots. A genetic algorithm is used to keep desired functionality by combining controllers that display the desired characteristics defined by a fitness function. With this mechanism the controller is ever changing and can adapt to changes in the environment.

One problem this leads to is that is necessary to have mechanisms that ensure the survival of already functioning genotypes. In some situations the temporal changes in the environment could lead to the extinction of desired traits. For instance the robots that start monitoring the new wing may have evolved a mechanism for safely navigating down the small sets of stairs in the old wing. When the robots enter the new wing it may contain steep stairs that are dangerous for the robots to navigate This could cause the stair mastering control mechanism to disappear quickly although it is still needed in the old wing.

One way to a better understanding of how such mechanisms can be designed is to examine what needs to be present in such a system for a given behaviour to evolve. Altruism among the robots is an interesting behavioural trait in this regard because it is a trait that can be useful for the population in a multi-agent system as a whole. As an example consider robots working on an arbitrary task in an environment where the supply of energy is unstable. This could be for instance mining robots on the surface of mars reliant on solar power. If the sun is blocked out in a sandstorm the robots could share the combined energy they have between them to keep up productivity. Altruism can be seen as being evolutionary counter-intuitive and is of interest because of this. Understanding the mechanisms that make individuals evolve behaviour that maximizes the utility of the population rather than maximizing the utility of the individual is important to be able to create control mechanisms in multi-agent systems that can make the system perform better as a whole.

1.1 What is Altruism?

This section gives a brief introduction to what altruism is and presents the most authoritative works on the subject in biology.

1.1.1 Altruism in Biology

Altruism can in short be described as one individual sacrificing its own fitness, meaning chances of survival, to increase another's. In the classic theory of evolution individuals are thought to maximize their own fitness to ensure the survival of their own genes, yet this behaviour where phenotypes actively decrease their own chances of survival is often seen in nature. For instance meerkats often have a single individual stand guard to watch for predators while the others eat. Many explanations on how this behavior is evolved through natural selection when individuals seek to maximize their own fitness have been proposed. The most prevalent theory in literature is the notion of 'inclusive fitness' outlined in the classic texts by Hamilton such as W. D. Hamilton [1963], Hamilton [1964a] and Hamilton [1964b]. Inclusive fitness includes not only the fitness of the individual, but also the number of offspring it has and is able to sustain. In short, inclusive fitness measures the success of the individuals in ensuring the survival of their genes. From this Hamilton proposed a rule for when altruism can be advantageous for an individual. An altruistic action is characterized by the cost C in form of decreased benefit, the benefit B given to the receiver and the relatedness r between the parties involved. Hamilton characterized the relationship between the three in the equation given in 1.1

$$C/B < r \tag{1.1}$$

It is common to distinguish between reciprocal and non-reciprocal altruism. The latter means that the altruists gets no immediate benefit from the transaction.Trivers [1971] gives an explanation for the mechanisms behind reciprocal altruism. This report focuses on non-reciprocal altruism. Lehmann and Keller [2006] develops a method of classifying models of what they call 'helping' in which there is a distinction between the act of cooperation and the act of altruism. The transaction between two individuals is seen as cooperation if there is an exchange of fitness benefits, either directly or indirectly over time through repeated interactions. To be altruistic, the exchange has to lead to a direct or indirect decrease in fitness for one of the individuals. Although the focal point of this article is altruism, many of the same mechanisms that evolve cooperation apply and are sometimes referenced. Montanier [2013] presents a partial review of the most recognized mechanisms that account for the emergence of altruism. In this review, the mechanisms are divided into four categories:

Kin-selection The individuals that benefit from the altruistic deed are closely related to the altruist and also harbors this capability, thus ensuring the survival of the gene.

Group-selection Groups are created randomly containing altruistic and egotistical individuals and the altruists help ensure the survival of the group as a whole. The groups are reorganized at random after some predefined amount of time has passed and without this the altruists would go extinct within their own group.

Kin-recognition Phenotypic traits are used to identify similarities in the genome, which altruistic individuals use to identify each other to gain selective advantage. kin-recognition was first proposed by Hamilton and further explored and named the 'Green Beard' effect in Dawkins [2006].

Environment-viscosity In viscous populations, there is a greater chance that the benefit of altruistic actions goes to closely related individuals. This can be seen as a mechanism that ensures kin-selection.

1.2 Research on Altruism and Cooperation in multi-agent systems

This sections gives an overview of the most relevant work on the evolution of altruism in multi-agent systems. Although the focus of this report is on evolutionary robotics, research from other areas are included when deemed relevant.

1.2.1 Cooperation and altruism among non-kin

Floreano et al. [2008] presents four different algorithms that may lead to altruistic cooperation. Both selection at the level of the individual and team selection is tested. The experiments simulate ants foraging for food items where two ants can bring back more food by cooperating than the two separately can by bringing a food item each. The associated cost is that each ant gets less food in return than when cooperating. Higher levels of altruism was observed when using team-level selection and more homogeneous teams had higher overall fitness.

1.2.2 Cooperation and altruism with kin-selection

Mayoh [2000] evolves altruistic strategies in iterated games inspired by game theory where the possible strategies are predefined in the experiments. The interesting point made in this paper is that it provides a model showing that reciprocal altruism can be a good strategy for maximizing utility even in interactions where the other's strategy is unknown, IE. without the use of a tag.

Cooperation among non-kin in organisms that lack the capacity to distinguish other altruists are accounted for in Barta et al. [2010].This is done by the introduction of the concept of generalized reciprocality. The paper makes the argument that internal state is a factor and that some organisms are more likely to cooperate if they were cooperated with in the last encounter. This is similar to the tit-for-tat strategy in prisoner's dilemma and the results are shown experimentally by introducing state and evolving this strategy under a range of conditions. On the other end of the spectrum, Dessalles [1999] explains this behavior through complex political constructs and sub-group competition. Cooperation in situations where individuals have the capacity to assess the intentions of others are described in Han et al. [2011] where the results support the conclusion that intention recognition promotes cooperation.

Montanier and Bredeche [2011] uses an experimental setup where autonomous robotic agents must forage for food and there is a chance that the situation of the tragedy of commons might occur. The fitness function is implicit by having the robots exchange genomes with every other robot it meets during a generation. The robot then chooses a genome to use at random from its list of genomes and uses a slightly modified version of this. This is interesting because low viscosity increases the fitness at the population level. Altruism is still observed and to a certain degree tuned by introducing a mechanism for kin-selection.

Ozisik and Harrington [2012] includes tags in the selective fitness model to account for some of its shortcomings.

1.2.3 Cooperation and altruism with kin-recognition

Turner and Kazakov [2003] explores how different mechanisms for sharing affect the spreading of altruism in a MAS. The agents have no explicit fitness function and their survival is dependent on a stochastic process. The altruistic gene is seeded into the population and they explore different degrees of kinship recognition, the most interesting of which being a scenario where the agents' phenotypic traits are determined from their genetic makeup, save the gene that determines altruism. The agents use this to judge how likely it is that they are closely related. This is similar to a 'green beard' effect, except that it's not discriminated against non-altruists, only those of sufficient genetic distance.

Experiments on kin selection in viscous populations were done by Dulk and Brinkers [2000] exploring the effect it has on the evolution of altruism. This concept is also explored from the viewpoint of theoretical biology in Joshua Mitteldorf and Wilson [2000]. The results show that altruists in the population tend to migrate less than non-altruists.

Hales [2005] proposes that tag-mechanisms obviate the need for repeated interactions or genetic relatedness to evolve altruistic behavior. The paper presents the hypothesis that mutating tags at a much higher rate than the behavioral strategy is a precondition for tag-mechanisms to work to avoid being exploited by free-riders. This hypothesis is tested experimentally with one-off prisoner's dilemma-games and the results support the hypothesis. The important thing to note is that in recognition based mechanism only the tag is important, not the actual relatedness of the individuals.

Spector and Klein [2006] demonstrates experiments using tags where the cost of the altruistic acts exceeds the benefits of the recipient. The experiments vary the parameters of genetic stability and territorial structure and shows that tag mechanisms can evolve altruism under a wide range of conditions. This provides support to tag mechanisms being a robust way to ensure the evolution of altruism.

Martijn Brinkers and Dulk [1999] did simulations of the evolution of non-reciprocal altruism with kin-recognition where the altruistic act was indeed self-sacrifice. Agents were placed on a grid and the grid had parts with land and parts with water. The goal was to forage for food, and agents could drive into the water forming a bridge between two pieces of land so that others could reach the food that existed on the other side. However, this was based on a very simple simulation where the genome evolved was the probability that an agent would drive straight ahead when there was water in front of it. The results showed that the probability increased when closely related individuals could benefit from it. This set up was based on a stochastic process and did not include the simultaneous evolution of other control mechanisms for the robots. The robots were only able to cross from one island to the other, not navigate the environment in any other way. The altruistic outcome was also a complete sacrifice where the agents that chose to be altruists died. This did not leave room to display different degrees of altruism.

1.3 Research question

Exploring the research on the artificial evolution of altruistic behavior and in particular the relationship between the evolution of altruism and the recognition of related individuals leads to the question of whether or not kin-recognition can be used as a way of ensuring the successful evolution of altruism in evolutionary robotics. At this point, it is important to keep in mind that recreating the conditions that evolve altruism in nature is but a mean to achieve the desired results in evolutionary computing and not a goal in itself. This means that the research question and the proposed research is not geared towards explaining the observations from nature, it is directed towards finding mechanisms that can be used to solve a problem.

The research question that arose is presented here:

Research question *Do kin selection and kin recognition help the evolution of self-sacrifice in evolutionary robotics?*

In this context, self sacrifice is thought of as the focal individual relinquishing chances of further dissemination of its own genes in order to enhance the the possibility of spreading the beneficiary's genes. Recognition of kin implies that the benefactor has a way of discriminating between those who have a genetic composition that is close to its own and those who do not. The literature shows that a large degree of altruism is rarely displayed without some form of explicit kin recognition. There is reason to believe that evolving self sacrifice with kin recognition is more successful than without.

Chapter 2

Method

To see if kin recognition has a positive effect on altruistic behaviour different means of recognizing kin will be tested against a baseline without any form of recognition. The focus of the experiment is on the difference between kin-oriented mechanisms and non kin-oriented mechanisms. The success of the experiments will be determined by the degree of altruism displayed compared to the baseline. This chapter describes the experiments to be used to determine if and how different kin-oriented mechanisms lead to different degrees of altruism.

2.1 Basic setup

To observe altruism a population of robots that can perform an altruistic action and an environment for the robots to interact in is needed. The robots need to have a control mechanism where the control of all the actuators are evolved by having the agents exchange genotypes that are combined and mutated to serve as the basis for the next generation of individuals. A simple way to model this is to make the robots dependent on a form of sustenance for survival and give them the the ability to give away sustenance. In the experiment a population of robots will forage for sustenance by collecting and consuming ”energy points” in the environment. The robots consume energy indiscriminately, meaning that they will consume all the energy they come across, and can not continue to survive in the environment without energy. A fixed maximum lifetime duration will be used to simulate the robots dying of old age to ensure the continuing evolution of the population. The robots will be able to mate with other robots they encounter which is how the mixing of successful genotypes is ensured.

2.1.1 Initial period

To separate the evolution of the foraging behaviour from the evolution of altruism the population will first be evolved without the ability to give away energy. In this preliminary period, the agents will consume energy points that are distributed in and generated by the environment. When an energy point is harvested by an agent it becomes inactive so that no agents can benefit from it. After a delay, the energy point is re-activated and can again be used. The populations that have a form of kin selection or kin recognition will be evolved with this trait active also in the initial period.

2.1.2 Second period

When the initial period is over and effective harvesting patterns have been established the agents will be given the ability to create energy points of their own. The robot generated energy points are like the energy points that are generated by the environment, but the robot who has generated a point can not consume it. The energy points created by the robots can only be consumed once and are never replenished. In this part of the experiment all the energy points created by the environment are removed to simulate a period of food shortage. This situation will be used to see if the different mechanisms implemented will lead to different strategies for sharing the available resources.

2.1.3 Desired behaviour

A successful outcome of the experiment would be if more robots survive for a longer period of time than in the baseline. There is also the criterion that the increased survival must be due to the robots distributing the available energy among themselves. The desired effect is that related robots share the energy resources in the environment in a more effective way than before.

2.2 The scenarios

2.2.1 Baseline experiment

In the baseline experiment the robots have no notion of kin-recognition or even that there are other robots in the environment at all. This experiment establishes the behaviour that is expected from the robots when they are simply given the ability to donate energy after first having evolved basic harvesting behaviour.

2.2.2 Kin recognition of nearest individual

In this experiment the robots are given the ability to assess how closely related they are to the robot that is the closest to them in geographical distance. The hypothesis is that if the robots that are more prone to donate energy when they are close to a related robot helps related robots survive, a group of related robots will help each other to survive in the environment and in that way ensure that the altruistic trait is carried one while the group remains alive. The representation of the genotypes of the robots will be given as a vector of numbers an thus the measure of the distance will be based on the formula in

$$\sum_{i=1}^{N} |RobotGenome_i - ClosestGenome_i|$$

2.2.3 Recognition of direction of closest related individual

In this experiment the robots are given the ability to discern the location of the closest related individual in the environment. The hypothesis is that the robots that tend to gravitate towards related individuals and are prone to altruism will have an advantage in that related individuals benefit from the altruistic deeds. The input value of this sensor will be the difference in the angle between the orientation of the robot and an absolute reference point and the angle between the robot and the closest related robot. This value will be given in degrees between -180 and 180. The closest related individual will be found by using the same measure of relatedness as in the kin recognition.

2.2.4 Kin-Selection in the evolutionary algorithm

In this experiment the robots will select the individual they have encountered among the other robots that is the closest to them genetically to use as a basis for procreation. The hypothesis is that since kin selection tend to make robots that are in close proximity of each other more related, the robots that are prone to altruism will give benefit to related individuals ensuring that the trait survives. Again, the same measure will be used for determining the most related genotypes.

2.3 The Robots

The robots that are simulated in the environment are based on the epuck model and are thought to be compact differential wheeled robots with sensors that sense distance in eight directions as shown in figure 2.1 .

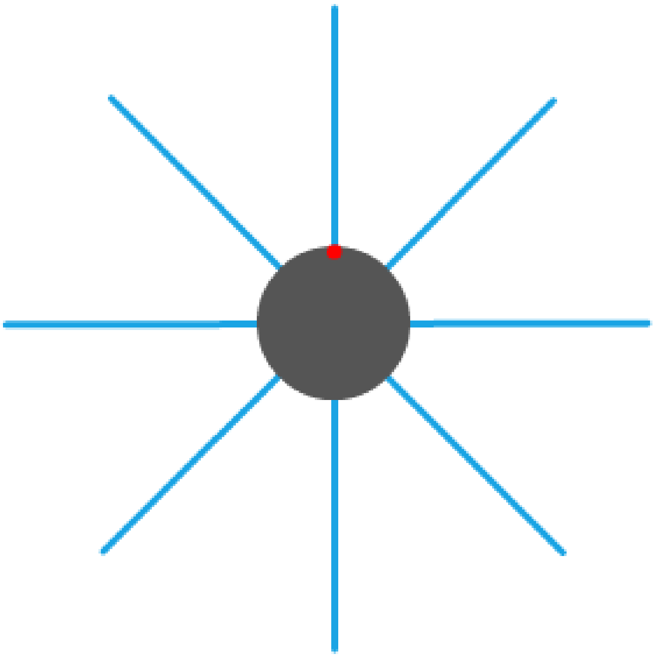

Figure 2.1: A single robot seen from above. The lines emanating from the body represent the reach of the distance sensors.

The robots also have a sensor that can sense if they are directly on top of an energy point. The sensory input the agents get are fed into the neural network that controls the actuators of the robots. There are four actuators: The two wheels, the ”mouth” that absorbs food and the output that creates energy points. Each robot is controlled by an artificial neural network that has 13 inputs that will be connected to the robot’s sensors.

2.3.1 Sensors and actuators

The robot has 12 sensors that all provide numeric input to the control mechanism. The function of the each sensor is given below:

- 1-8: Distance sensors
- 9: Direction to nearest energy point

- 10: Distance to nearest energy point
- 11: Energy level
- 12: Dependent on scenario

The robot has three actuators, two wheels used for locomotion and an output for the energy points.

2.4 Artificial Neural Networks

ANNs are computational entities that are inspired by how the brain does computation. In the brain, a network of neurons acquire knowledge through the body's receptors and maps the perceptions it receives to a given action. Learning is achieved by strengthening the inter neuron connections, known as synaptic weights. Haykin [1994]

One of the key reasons using a neural network is beneficial in this problem is that one of the great advantages of neural networks is that contextual information is taken into consideration. All the neurons in the network are affected by what is happening on a global level and therefore a given response may be elicited according to context. In this case, the choice of relinquishing energy should be affected by whether or not there are other robots nearby and perhaps also how closely they are related.

Artificial neurons have a series of inputs that are altered according to the weight of the input. This weight is analogous to the strength of the synaptic connection. There is also often an extra input that is constant and is known as a bias-weight. The summation of this is fed to an activation function that determines the output of the neuron. The output of one neuron can be fed as part of the input to another neuron and this is how the network is built. A neuron can also use its own output as an input, effectively giving the neuron memory.

The ANN that the robots are controlled by is a multi-layer perceptron with three hidden neurons and three output neurons. The output neurons control each of the wheels and has a binary output that decides if energy should be dropped or not.

Figure 2.2 shows the schematic drawing of the artificial neuron used by the robots in the baseline and the kin selection scenario. The unused sensor input is set to be 0 at all times.

The ANN for the kin recognition and kin seeking scenarios are show in figure 2.3 .

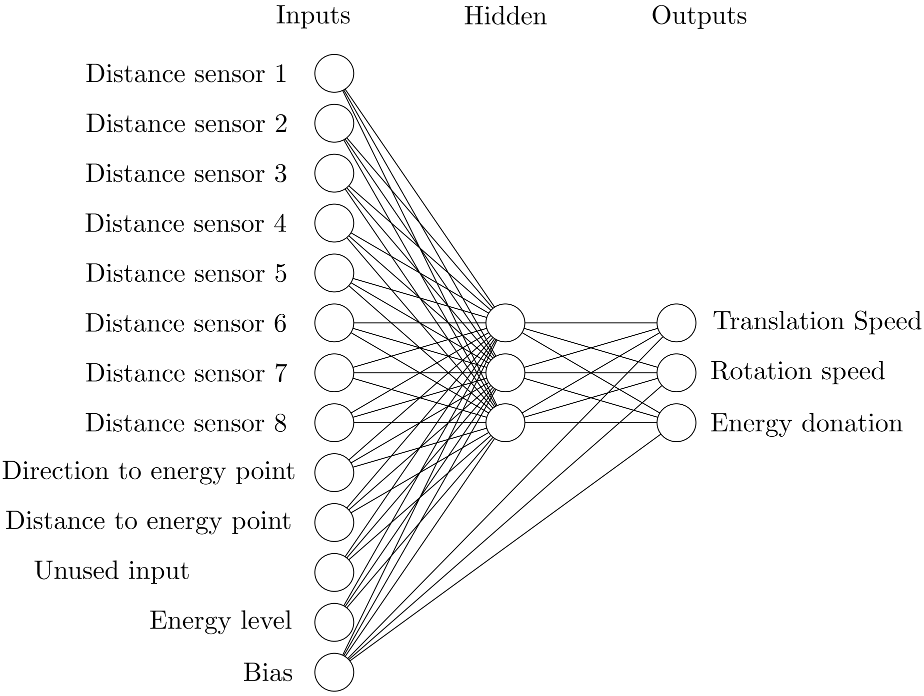

Figure 2.2: ANN used by the baseline and kin selection

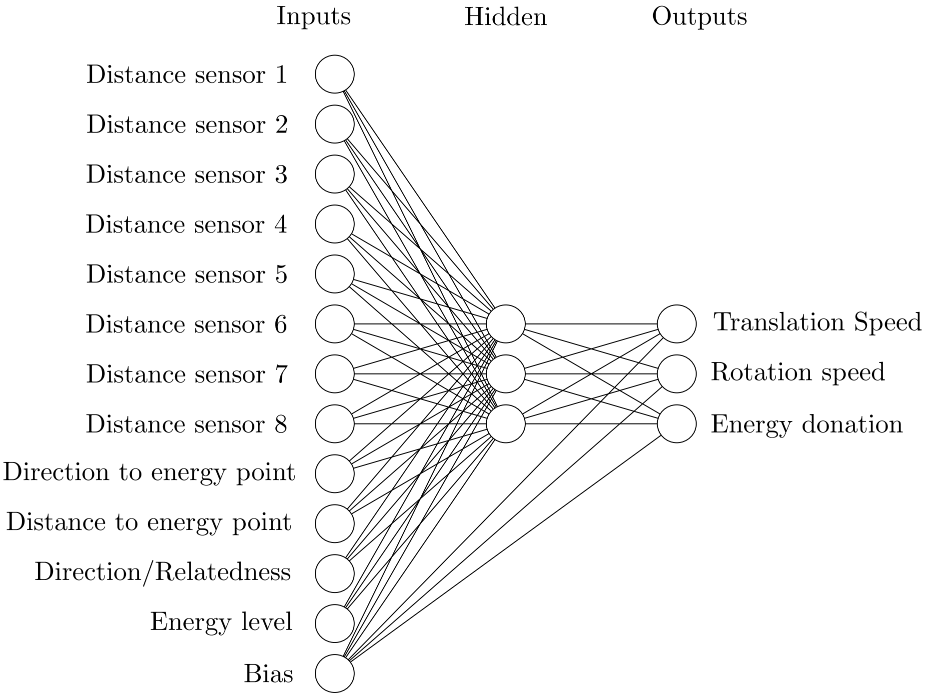

Figure 2.3: ANN used by the kin seeking/recognizing population

2.5 The Evolutionary algorithm - mEDEA

The evolutionary algorithm to be used needed to be both robust to change and have a fitness function that rewards survival and spreading of genes. The reason for this is that the algorithm should be designed to reward selfish individuals on the individual level so that the altruistic behaviour arises as an evolutionary response that increases inclusive fitness. For this reason the mEDEA-algorithm was chosen. The mEDEA algorithm is presented in pseudo code in algorithm 1

Algorithm 1 The mEDEA algorithm

```
genome.randomInitialize()
while forever do
    if genome.notEmpty() then
        agent.load(genome)
    end if
    for iteration = 0 to lifetime do
        if genome.notEmpty() then
            agent.move()
            broadcast(genome)
        end if
    end for
    genome.empty()
    if genomeList.size > 0 then
        genome = applyVariation(select_random(genomeList))
    end if
    genomeList.empty()
end while
```

In the mEDEA algorithm each agent has a list of genomes. Every time an agent encounters another agent they add that agent's genome to their list of genomes and when an agent is reactivated it chooses a genome from it's list of genomes that will serve as the basis for the new genome of the agent. The genomes are mutated as in regular evolutionary algorithms and the selection scheme can also vary. The fact that survival and dissemination of genes is an implicit demand of the mEDEA algorithm makes it a great fit for the experiment. The better the individuals are at spreading their genes, the greater are their chances to pass on their genes. This closely mimics the way evolution works in real life. Having an implicit fitness function that partially rewards for the trait we are after is having traits appear by design rather than by necessity. An agent is deactivated when it runs out of energy and reactivated when another agent passes nearby. An illustration of the exchange of genomes is shown in figure 2.4

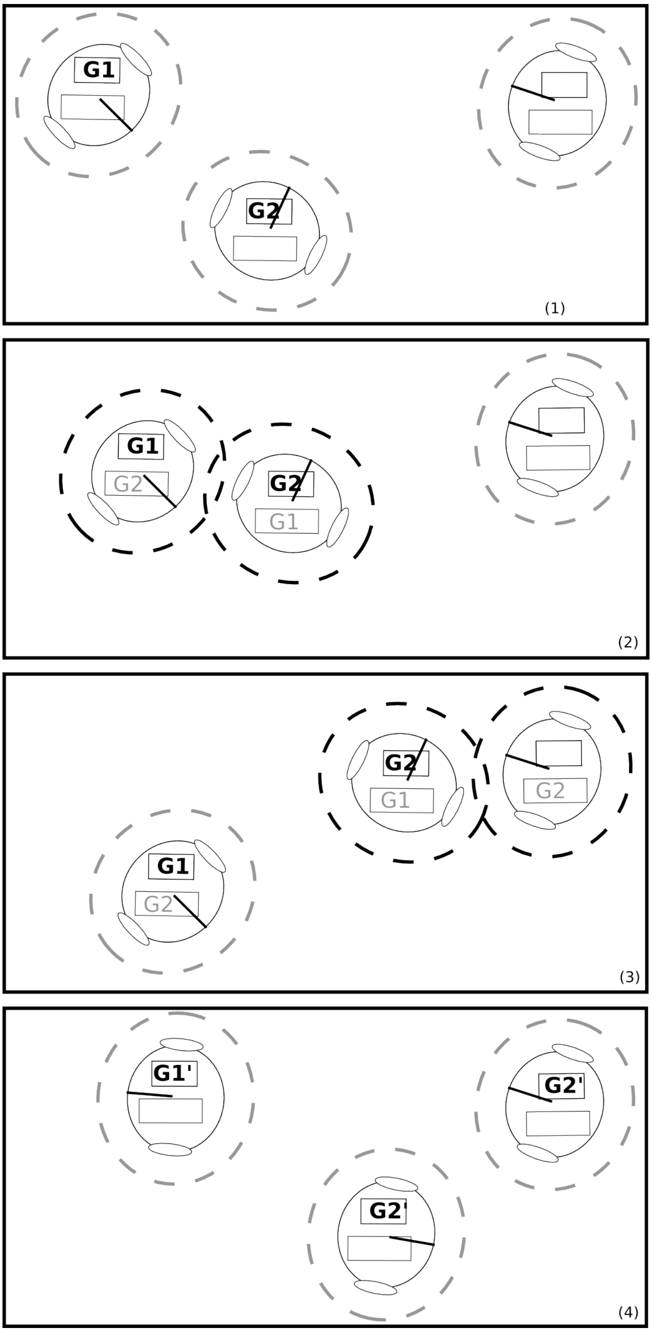

Figure 2.4: Sequence showing how genomes are exchanged in the mEDEA-algorithm

2.6 Donating Energy

The agents each have an output neuron that outputs a floating point value. If the value is above a predetermined threshold the agent creates an energy point in the environment that it cannot utilize for itself. The energy points that are created are never replenished unlike the energy points that are intrinsic to the environment. The amount of energy donated is set to be a predetermined number. This was chosen to simplify the experiments, but ideally the amount of energy donated should be determined by the output value of the neuron.

Using a predetermined value relieves the model of biological accuracy, but it allows for greater control and understanding of the parameters that are needed for the wanted behaviour to occur, which is the object of the experiment. Early initial tests showed that linking the amount of energy donated in each time step unsurprisingly led to the first generation of agents committing mass suicide in the first few time steps since the output value from the beginning is random. It is a reasonable to assume that the insects or animals the robots model already have evolved an inclination towards not dropping food and that this should only happen when a certain sensory input is provided.

2.7 The environment

The environment the robots inhabit is a large two dimensional square with a few obstacles scattered around. Very little exists in the environment and the robots roam around freely. A screen shot of the environment can be seen in figure

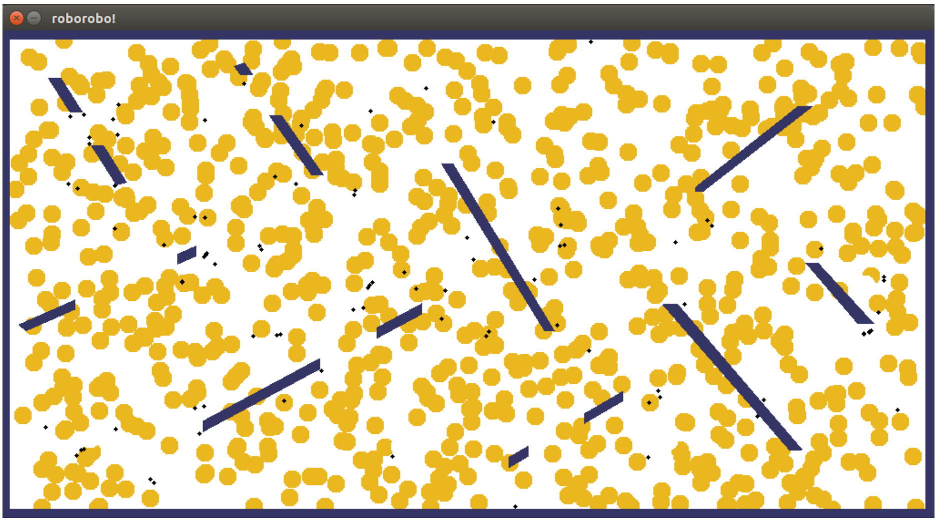

Figure 2.5: Screen shot of the robots in the initial period. The colored dots are the the energy points created by the environment, the black dots are robots and the lines are walls

2.8 Important parameters for the initial period

The complete properties file for the experiment can be found in the appendices.

The robots start out with a total of 100 units of energy and a generation lasts 400 iterations. 1 unit of energy is spent per iteration which gives the genome 1/4 of a generation to prove itself.

Energy expenditure	1
Initial energy	100
Iterations/generation	400
Energy points	100
Energy point value	50
Revival energy	400

Table 2.1: Important parameters for the first experiment

2.9 Important parameters for the final period

The threshold that the output of the donation neuron needs to exceed for a donation to occur is set to 0.7. Since the initial output value of this neuron is not a factor in the initial evolution of the robots it is to be expected that 3 out ten of the robots will become donors immediately and the others won't Introducing the trait in this way is artificial but it if the trait has a negative enough impact on the fitness of the individuals the trait will soon disappear. The energy expenditure in the altruism part of the experiment is set to 0.005 per iteration. The initial energy of the robot is set four times higher than in the initial period so that there will be enough time for the altruistic robots to meet other robots and propagate their genes. The initial tests showed that the altruistic robots would often give away so much energy in the beginning causing them to die out before being able to spread their altruistic genes. This also caused the entire population to go extinct shortly after. In this second period the robots spend 0.005 per iteration which makes the total expenditure of energy per generation 20 units for each robot. This means that they can survive for 200 generations without needing food provided they don't donate energy. This value is set low to ensure that the robots survive long enough that evolution can occur.

For the first experiment the number value of each energy point to be generated by each robot was set to be 50. This means that the robots can run out of energy if they create more than 16 energy points in the first generation. This number was chosen to be low enough that not all robots that are inclined to donate energy will die, but high enough so that the energy point provides useful sustenance for other robots.

The experiment is run for 400 generations to see what happens when the robots are close to running out of energy altogether, but the main period of interest is before this when the robots need to distribute the energy they have among them in order to ensure that all the active robots survive as long as possible.

Donation Threshold	0.7
Energy Point value	50
Energy expenditure	0.005
Initial energy	400
Iterations/generation	400

Table 2.2: Important parameters for the final period

2.10 Experimental setup

All the experiments were run on an Intel Centrino 2 clocked at 2.26 MHz. For each setting each experiment was run 100 times and the results computed as an average over those runs. On average, a single complete run of one experiment with both the initial period and the final period took approximately 30-35 minutes. To implement the experimental environment described an existing system that fulfilled many of the requirements was modified. The system that was used was Roborobo which is a 2D robot simulator based on the epuck/kephra model written mainly by Nicolas Bredeche with assitance from Jean-Marc Montanier and Leo Cazenille. Roborobo is written in C++ and is described in detail in Bredeche et al. [2013] This system was chosen because it was available in open source and because it provided a lot of the functionality that was needed for the experiment:

- Ready made environment for simulating small robots
- Integrated code for neural networks
- Built-in evolutionary algorithm functionality

The graphs were created using the Java library JFreeChart available at `http://www.jfree.org/jfreechart/`

Chapter 3

Results

In this chapter the results from the experiments are presented. First a collective assessment is given by looking at results from all the scenarios plotted on the same graph. The results from the four experiments are presented in turn and the same graphs are shown for all the experiments.

- The amount of agents over time
- The amount of agent generated points created and consumed
- The amount of energy available in agents and points

For all graphs the standard deviation is shown as a shaded area beneath the plot.

3.1 Assessment of the success of the kin oriented mechanisms

This is the period in which the altruism is introduced. The graph can be seen in figure 3.1. The Y-axis represents the number of active robots at the start of the generation represented on the X-axis. All the kin mechanisms have less robots alive than the baseline after the first period of 10 generations. Some time after 200 generations all the kin mechanisms have on average the same amount of robots alive except the kin recognition scenario which is slightly lower. This shows that the decline in the populations in the kin mechanisms scenarios happens slower than in the baseline. At the end of the 400th generation all the kin mechanisms have more robots alive than in the baseline. This is shown more clearly in the detail in figure 3.2. This graph shows the final generations of the experiment.

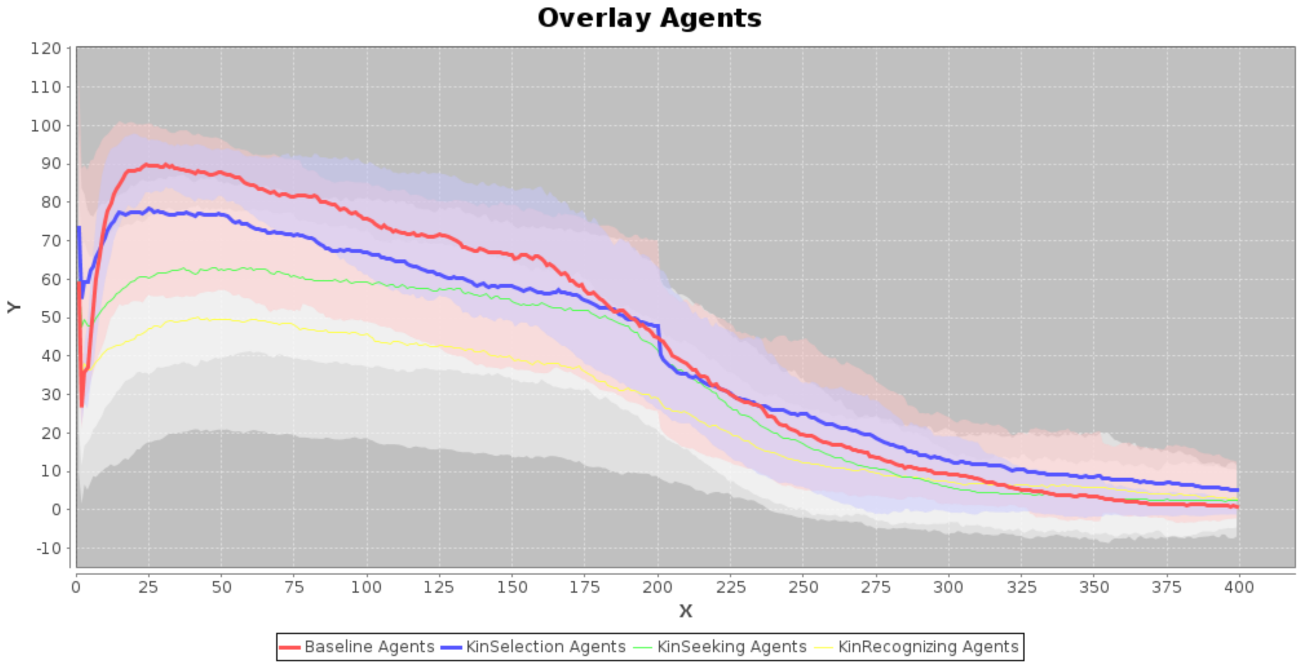

Figure 3.1: Graph showing the number of agents in all the runs

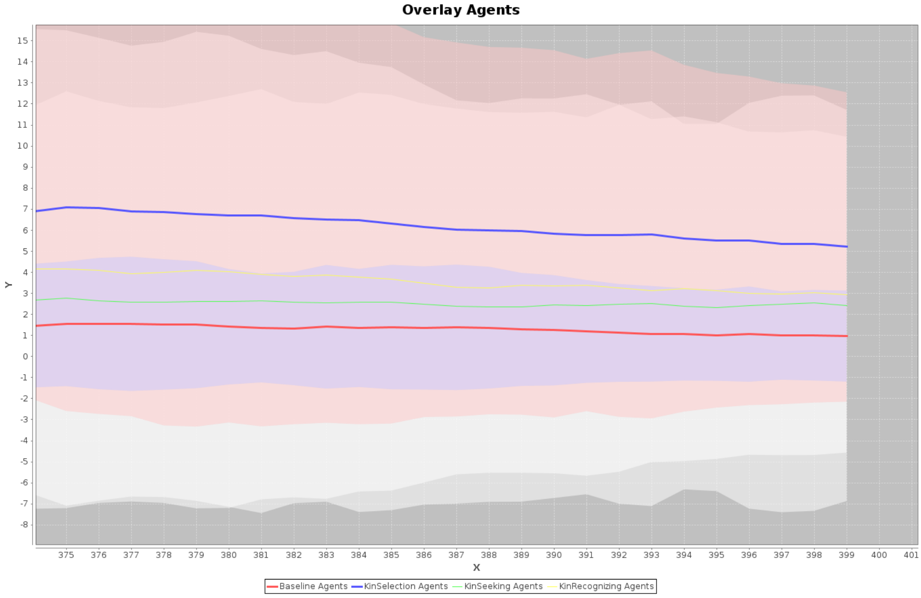

Figure 3.2: detail of graph of the number of points created for each scenario

This happens because there are more energy points being produced each generation as can be seen in figure 3.16. Here the Y-axis represents the number of energy points created in the generation represented by the X-axis. The kin selection mechanisms all produce more energy points than the baseline between the 10th and the 250th generation. The kin seeking population creates slightly more energy points than the others explaining why they remain the most successful population for a large portion of the experiment. In the period from 120 to 170 the kin selection population creates more points than the others which explains why it ends up as the most successful population towards the end of the simulation. A detail of this is shown in figure 3.17 Indeed there is more energy available in the environment relative to the number of agents in the kin oriented scenarios. This is shown in the graph in the figure 3.3. In this graph the Y-axis represents the sum total of energy available in energy points each generation represented by the x-axis. We see in this graph that the kin selecting population has the most amount of energy available to them. The kin seeking population and the kin recognizing population both have roughly the same amount of energy available as the baseline. As we saw in the graph in figure 3.1 they have a smaller population than the baseline for a large part of the experiment. This means that they have more energy available per robot in the active population.

The cause of the large drop in the population size in all the scenarios is the number of robots that give away all their energy. This happens because the altruistic trait is new and a donation strategy has not been evolved. Since a donation strategy has not been evolved yet, the donations happen at random. The number of robots is reduced by a different amount in all the populations. This could be explained by the different levels of homogeneity in the populations but no measurement of this was made to support this.

In the next sections the peculiarities of each scenario are shown.

3.2 Baseline

Figure 3.4 shows the graph displaying the number of active robots in the environment at the end of each generation for the baseline. The number of robots quickly rises again as the remaining active robots who are not giving away energy consume the energy that has been dropped. The robots then gradually become inactive as the robots with the least amount of energy expend all their energy while there is less and less energy available in the environment as shown in figure 3.5 which shows the sum total of energy in the robots and the sum total of energy in energy points in the environment over time. Figure 3.6 shows the number of points created and consumed. It is clear that after the initial period there is very little energy being brought into the environment as very few new energy points are created.

3.3 Kin recognition

Figure 3.7 shows the graph with the number of active robots in the kin recognition scenario superimposed on the graph with the number of active robots in the baseline from 3.4 for reference. The Y-axis represents the number of active robots in the generation represented by the X-axis. The drop in number of robots is less dramatic than in the baseline, but in return the rise in number active agents in the subsequent period is substantially less. There were however no measurements of the homogeneity of the populations at the start of the second period made that can be used to support this. The graph in figure 3.9 shows that for a large section of the duration of the experiment the amount of energy in the system is constant although points are being consumed.

The lower fluctuation in agents in the beginning could be because the surviving robots have a similar genetic make-up as the ones that die. More robots keep on creating energy points after the initial period. The graph in figure 3.8 supports this by showing that roughly 50 % more points are created in the first

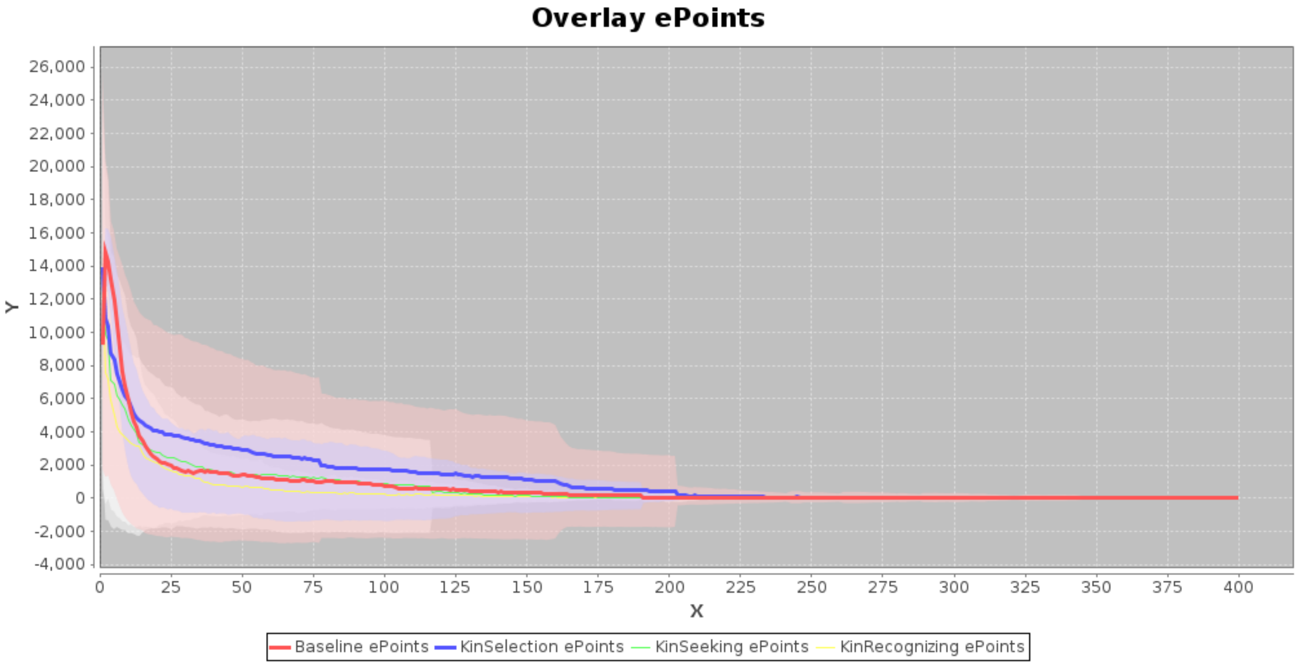

Figure 3.3: Graph showing the sum total of energy available in energy points over time

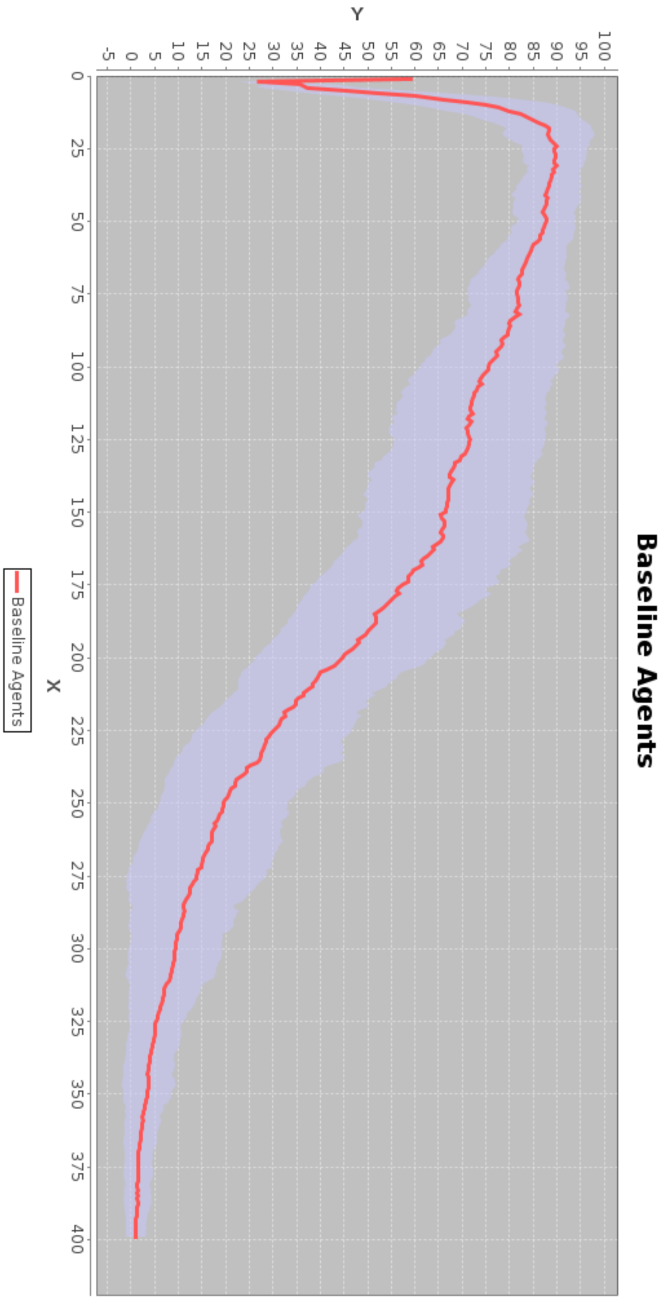

Figure 3.4: Graph showing the number of active robots in each generation for the baseline

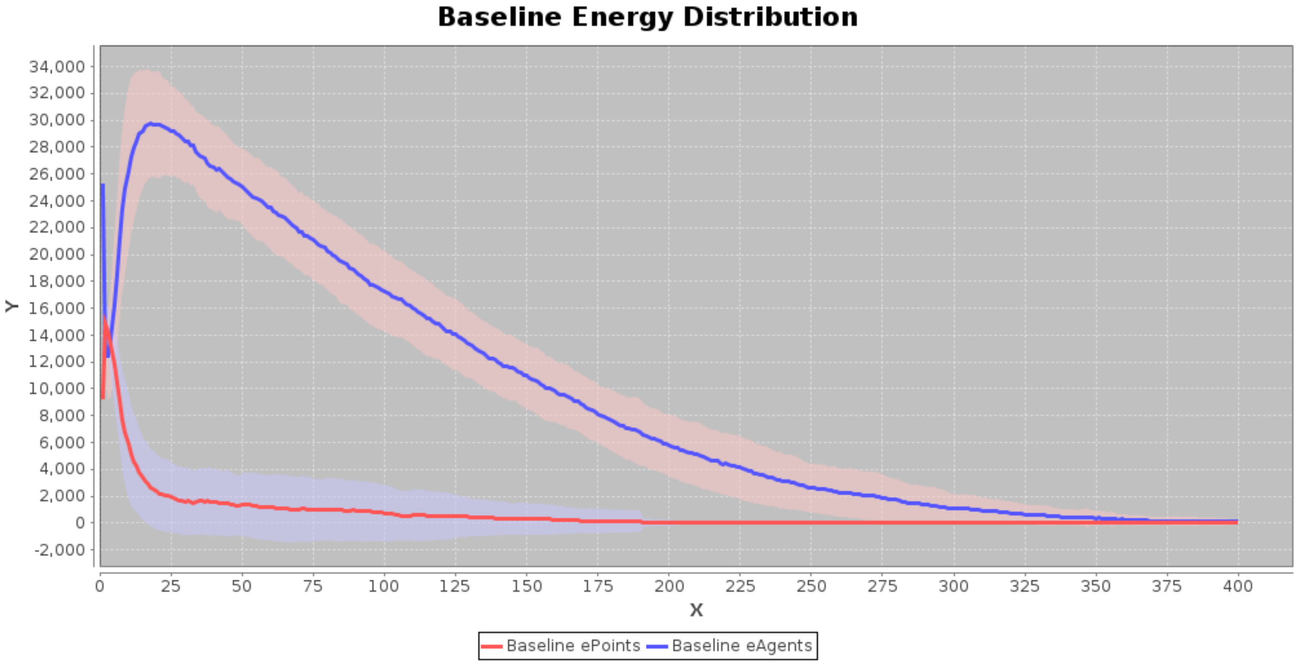

Figure 3.5: Graph showing the amount of energy in the system and the amount of energy in the robots for the baseline

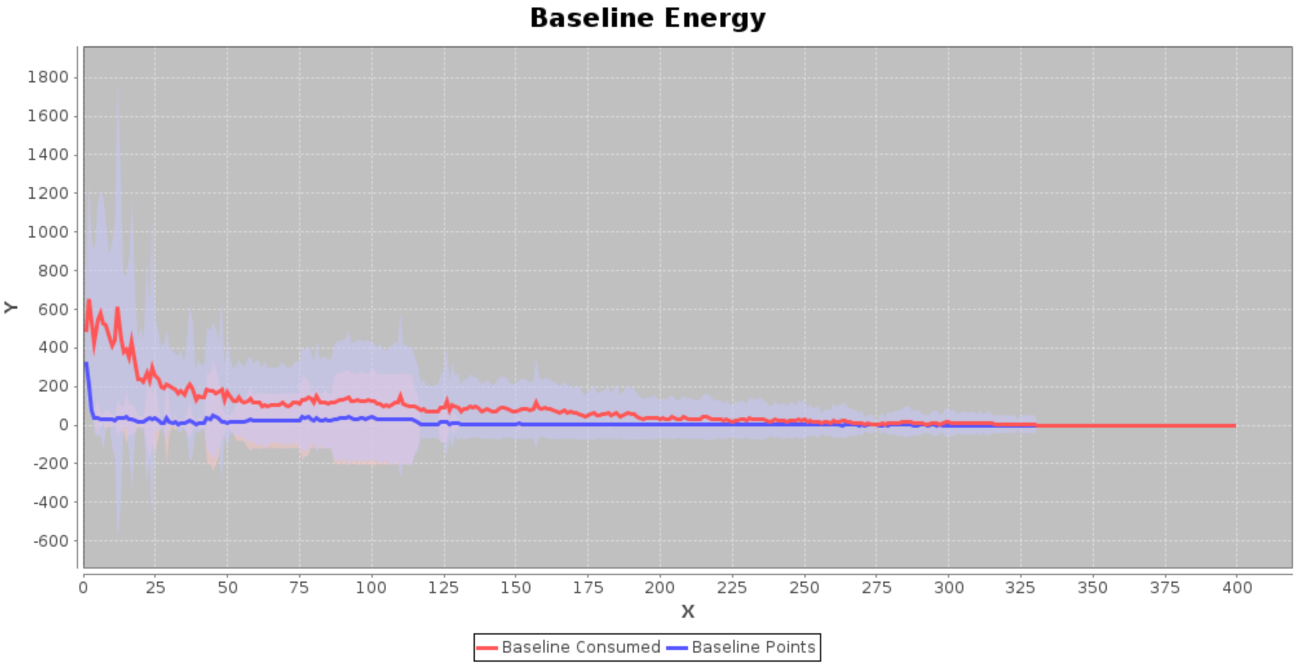

Figure 3.6: Graph showing the number of points created and consumed each generation for the baseline

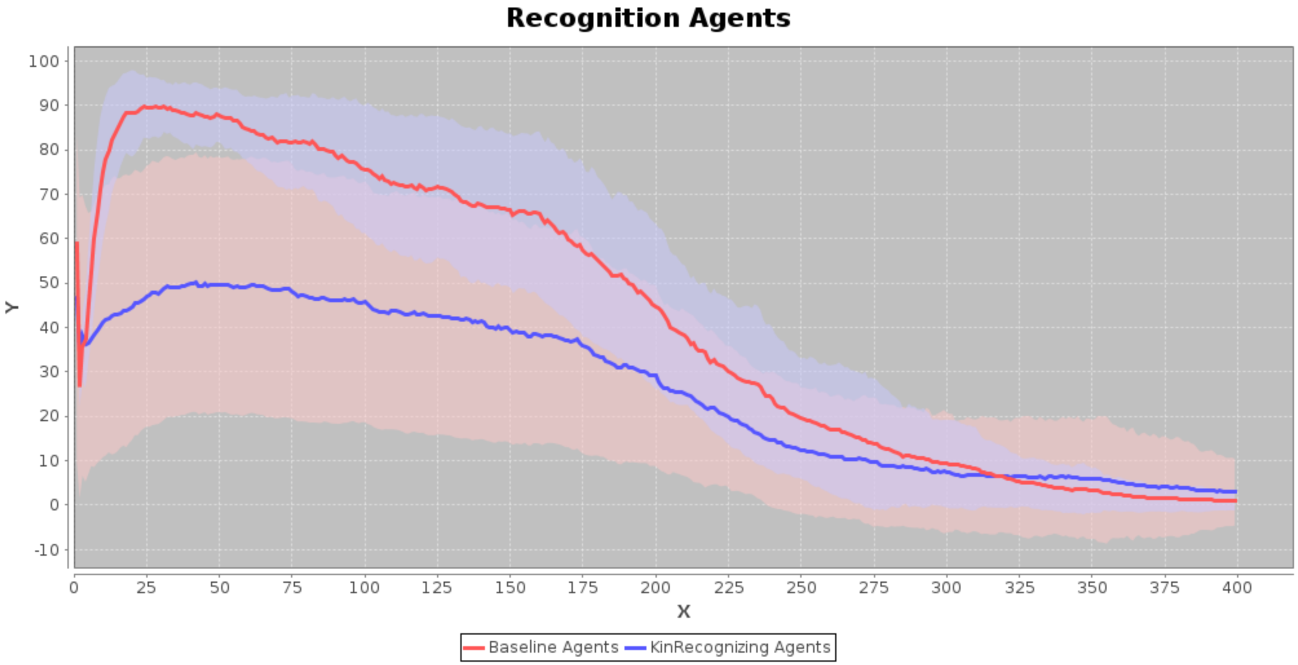

Figure 3.7: Graph showing the number of active robots in each generation for the kin recognition scenario

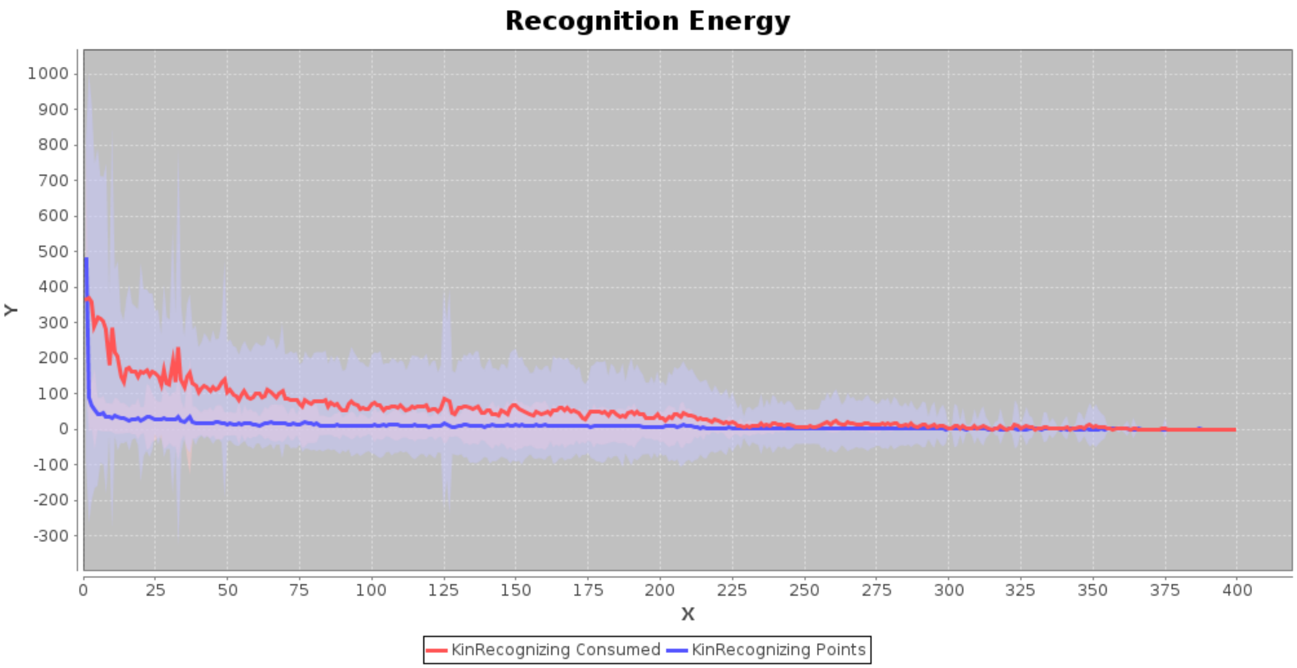

Figure 3.8: Graph showing the number of points created and consumed each generation for the kin recognition scenario

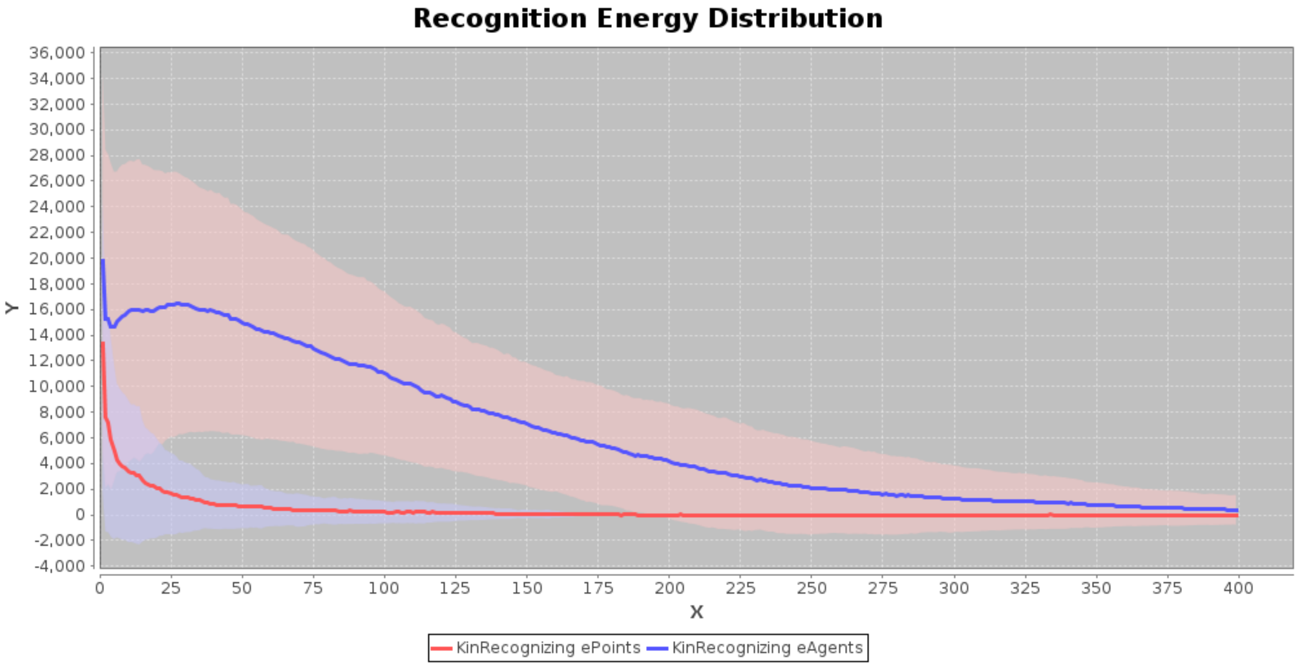

Figure 3.9: Graph showing the amount of energy in the system and the amount of energy in the robots for the kin recognition scenario

25 generations which is the time it takes the baseline to reach its maximum population.

3.4 Kin seeking

Figure 3.10 shows the same graph as in figure 3.7 for the kin seeking scenario. The shape of the graph is very similar to that of the kin recognition scenario shown in 3.3 only shifted upwards on the y-axis, having approximately 10 more active roots on average. The mechanisms behind the shape itself is thought to be similar to that of the kin recognition graph and the cause of the shift is simple. The graph in 3.11 reveals that more energy points are created in the kin seeking scenario. The reason for this is unclear, but the hypothesis is that there is an even more homogeneous population evolved in the initial period in the kin seeking scenario.

3.5 Kin selection

The graph in figure 3.13 shows that it's initially the most successful of the kin-oriented scenarios. The kin-recognition scenario has the largest population of the three and the decrease in population size is less than in the baseline. Curiously the population size is suddenly dropped exactly after 200 generations. This could be because there are sub groups in the population where altruism is never seen and the robots thus have no means of consuming energy. If the viscosity in the environment is high enough they never encounter altruists and use only the amount of energy they are given from the beginning. This energy lasts exactly 200 generations as mentioned in section 2.9

Of the three kin-oriented methods the simple kin selection was the most successful. The reason for this is that it creates the highest number of points in the beginning while still managing to maintain the population with the highest number of point donations throughout the duration.

3.6 Similarities of kin seeking and recognition

The graphs displaying the number of active agents reveals that the shape of the curves for kin seeking and kin recognition look remarkably similar. The detail of the graph shown in figure 3.18 shows that they display the same pattern of falling before rising slightly and then falling again before they ascend to the highest point. This could be an indication that the populations evolved by the kin seeking population and the kin recognizing population may have a similar constitution.

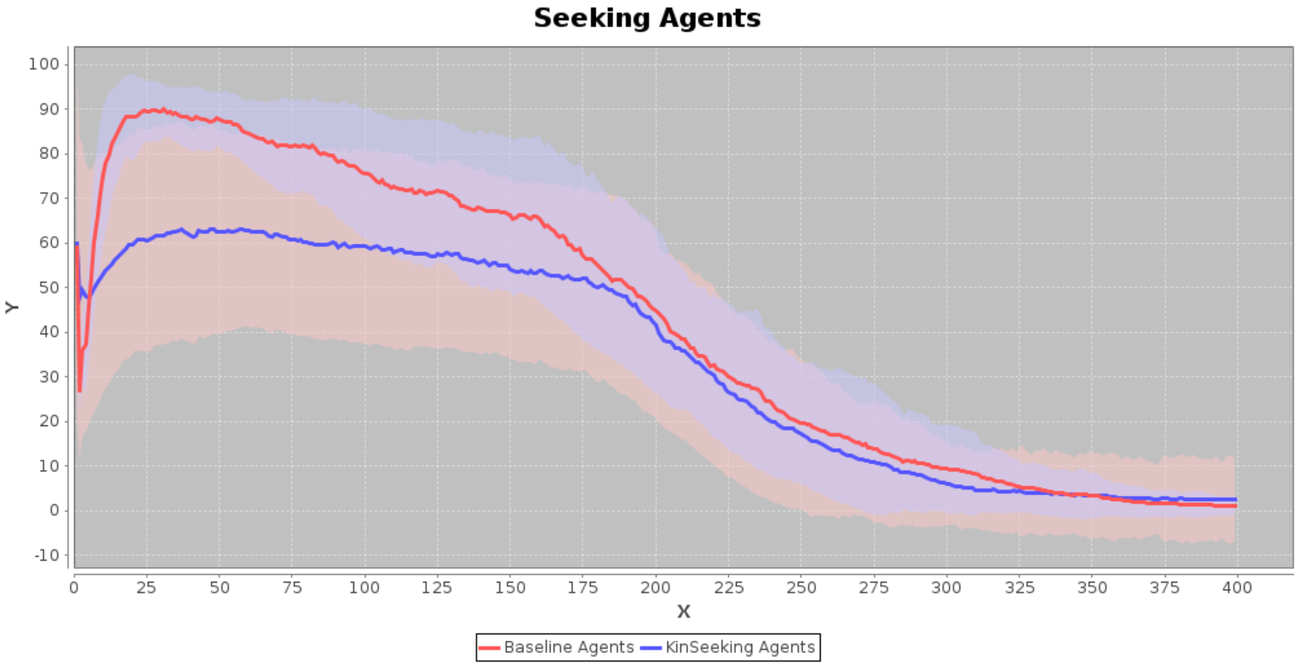

Figure 3.10: Graph showing the number of active robots in each generation for the kin seeking scenario

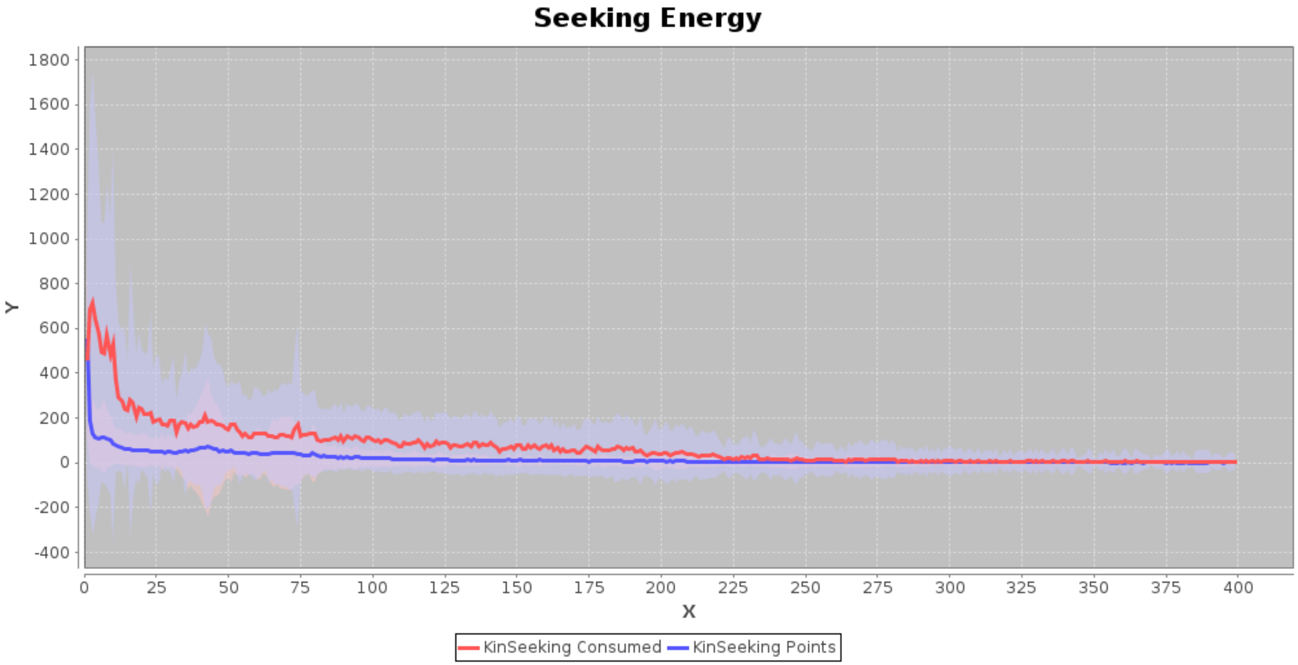

Figure 3.11: Graph showing the number of points created and consumed each generation for the kin seeking scenario

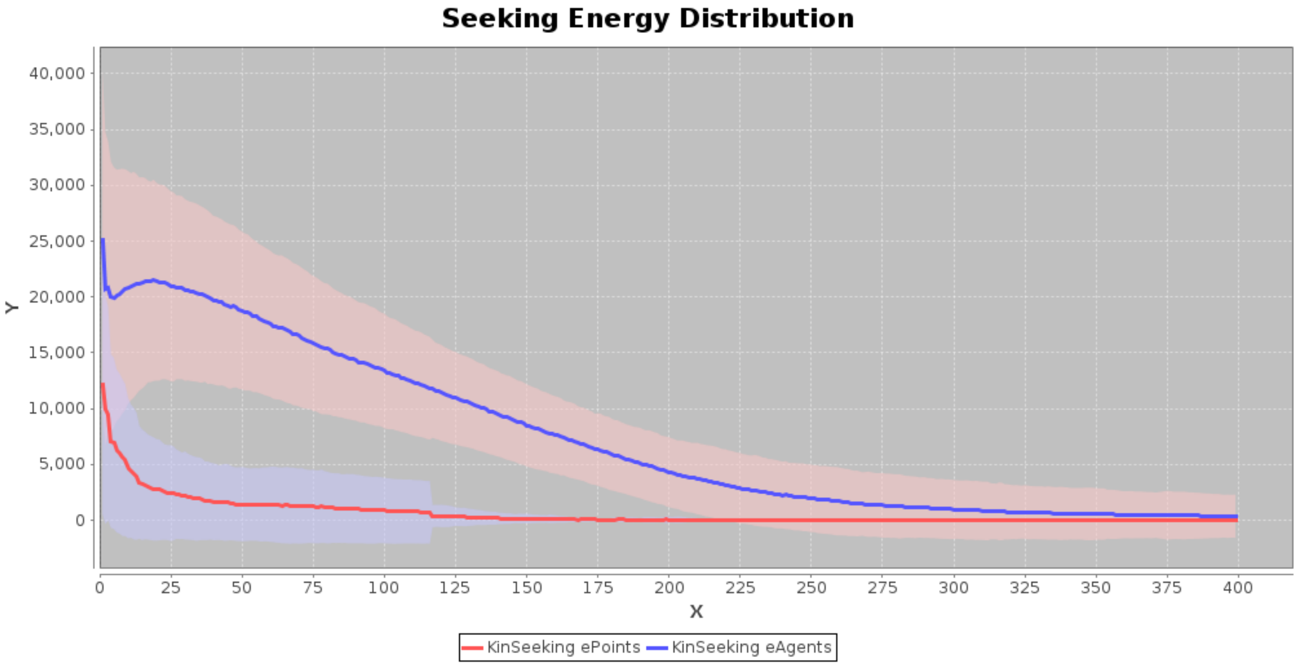

Figure 3.12: Graph showing the amount of energy in the system and the amount of energy in the robots for the kin seeking scenario

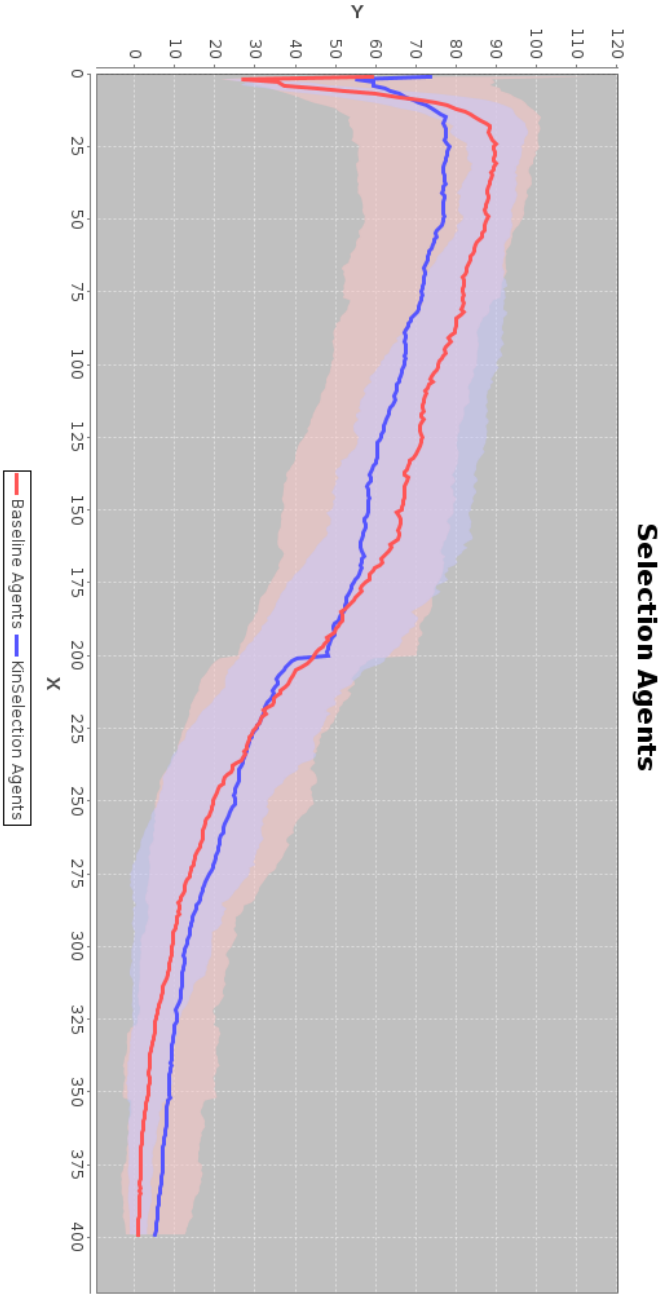

Figure 3.13: Graph showing the number of active robots in each generation for the kin selection scenario

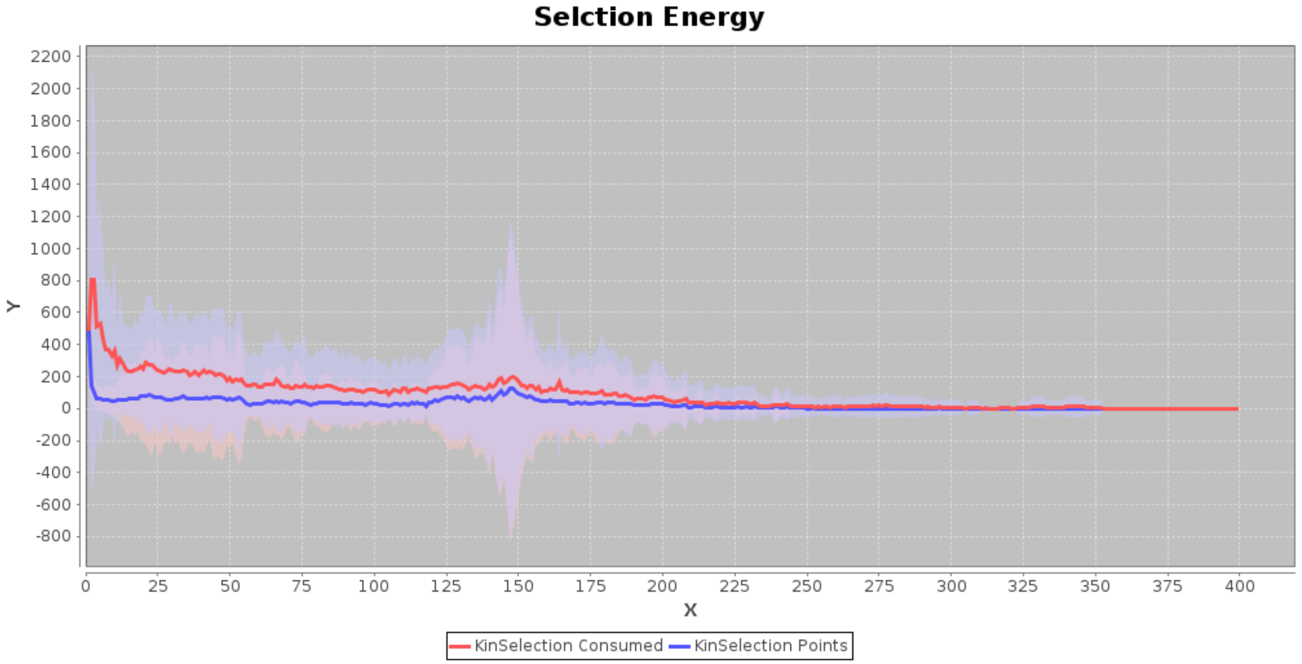

Figure 3.14: Graph showing the number of points created and consumed each generation for the kin selection scenario

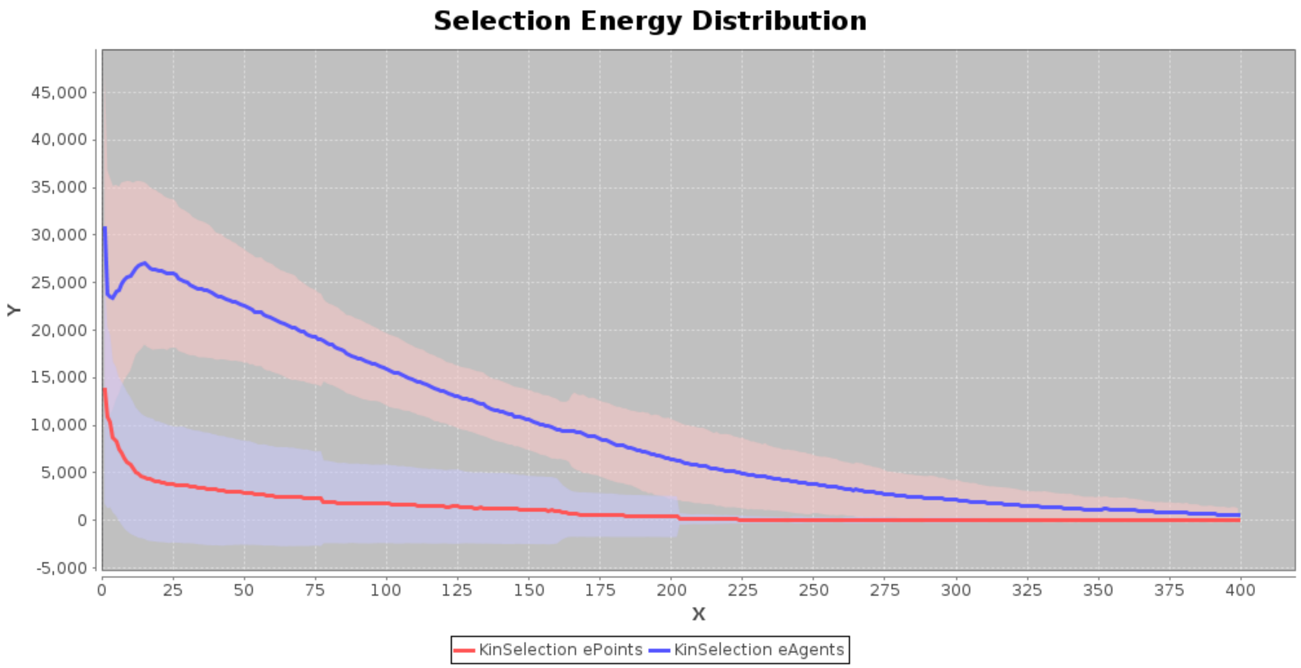

Figure 3.15: Graph showing the amount of energy in the system and the amount of energy in the robots for the kin selection

3.7 Conclusion

The results presented in the previous sections suggest that kin-selection and kin-recognition lead to higher degrees of altruism in evolutionary robotics holds. The research question was:

Research question *Do kin selection and kin recognition help the evolution of self-sacrifice in evolutionary robotics?*

Kin selection and kin recognition seem to have helped the evolution of self-sacrificial behaviour in the experiments done. The evidence is not strong enough to be conclusive and more research needs to be done. Some suggestions on what should be the focus of future studies is presented in the next section.

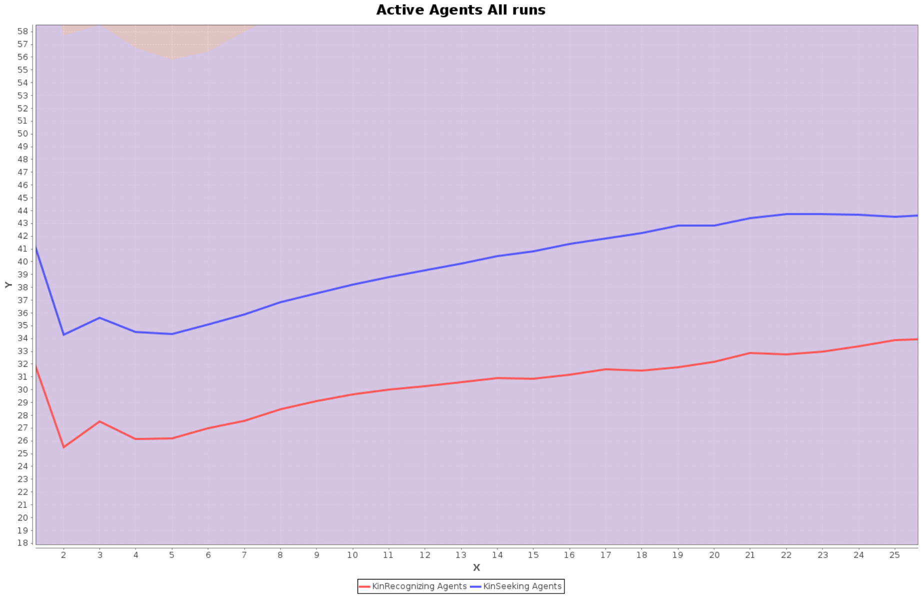

Figure 3.18: Detail of the first few generations in the kin recognition and kin seeking scenarios

3.8 Future work

The results from the experiments leave room for much to be explored. This section gives a few suggestions on what should be pursued further.

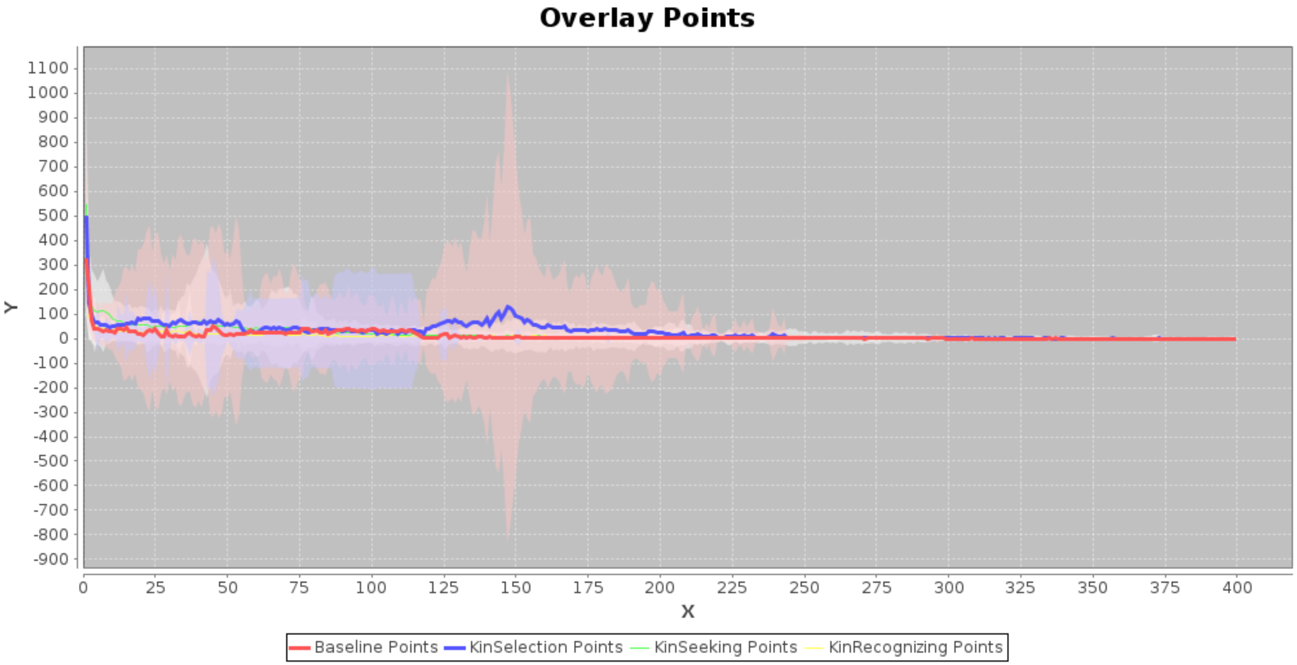

Figure 3.16: Graph showing the number of points in all the runs

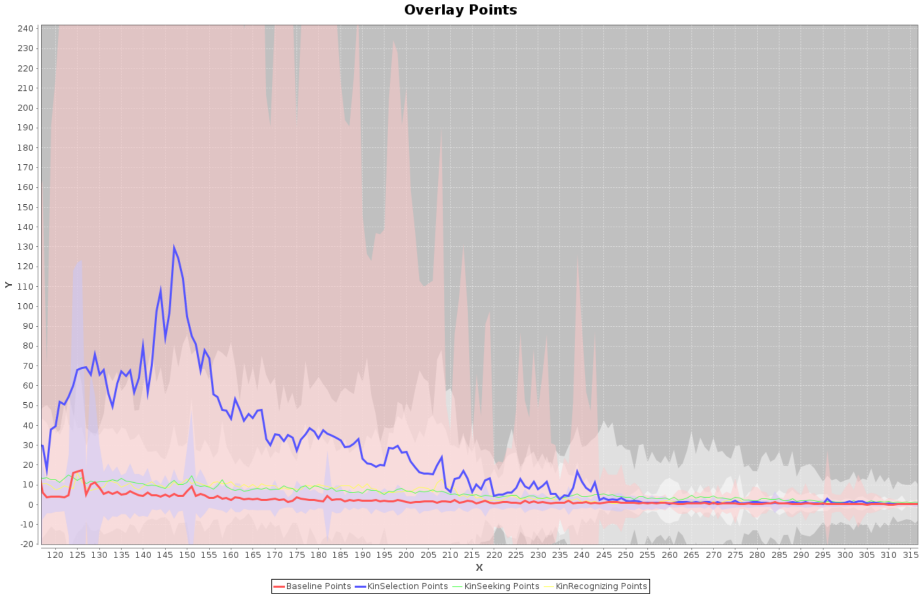

Figure 3.17: detail of the graph of the number of points created for each scenario

3.8.1 Tracking of genetic homogeneity

A likely hypothesis is that the difference in the amount of energy donated to the environment is connected to how homogeneous the population is. Future work could involve tracking the homogeneity of the population as a whole to see how it coincides with the donation of energy, if there is any correlation at all. This tracking could involve tracking the homogeneity of local groups in the population where the energy points are being created to see if there is a difference in the sub groups in the environment. If it can be shown that some local groups produce altruists a challenge would be to device a mechanism for spreading these genes since high viscosity contributes to the development of altruism.

3.8.2 Advanced version of kin seeking algorithm

The kin seeking algorithm seems promising and it would be interesting to run an experiment where the robots are given the direction of the largest concentration of related individuals. In this scenario the robot may seek out a group of robots that has a similar genotype. The hypothesis is that this would lead to more robots with altruistic inclinations profiting from the altruism when altruistic individuals group together. The challenge would be to find a purposeful way of grouping the robots together when assessing which area has the largest concentration of related individuals. One way of doing this could be to partition the environment into sections where the average degree of relatedness is calculated for each agent for each section. However, this method makes it more challenging to transfer the method to situated agents as it requires each of the robots to have a mapping function. Assuming the robots broadcast their whereabouts this could be solved by sectioning a circle surrounding the agents.

3.8.3 Advanced version of the kin recognizing algorithm

The kin recognizing algorithm could be expanded upon by having the agents take into account how related the are to all agents that are within close enough distance to transfer their own genome. This could provide a higher chance that the robots would give away energy when related agents are close enough that they may benefit from the donation. Another benefit of this method is that it makes use of the already necessary functionality in the robots to broadcast their genome to all agents who are close enough. This increases the chance that related individuals will be deprived of the energy and in as a consequence giving away energy is less likely to increase the inclusive fitness. In future experiments the way of donating energy could be changed to a direct transfer of energy between the robots. This way, robots could distinguish between who they give energy to.

Appendices

Appendix A

Systematic Literature Review Protocol

The systematic literature review was performed using the guidelines for systematic literature review in software engineering presented in Keele [2007]. The review protocol is presented along with the documentation of each step. The literature review process is divided into 8 steps:

Step 1 *Defining review questions*

Step 2 *Defining the systematic literature review protocol*

Step 3 *Search for relevant studies*

Step 4 *Selection of studies*

Step 5 *Quality assessment*

Step 6 *Data Collection*

Step 7 *Data synthesis and analysis*

Step8 *Dissemination*

A.1 Defining the Review Questions

The first step in the systematic review process was to formalize the the goal of the review into review questions that the review is meant to answer. The goal of the review was to answer the following questions:

RQ1 *What are the mechanisms that allow altruistic behavior to evolve?*

RQ2 *What are the most important factors in determining the degree of altruism displayed?*

RQ3 *Which methods show the most promise in achieving self sacrificial behaviour in artificial evolution?*

A.2 Search for Relevant Studies

To perform the search in a systematic way I compiled a list of of relevant sources which would be the subject to systematic query. I decided to use the list compiled in Lillegraven and Wolden [2010] as a starting point as it presented a list of relevant sources both for research on computer science in general and had already been used to find sources in Artificial Intelligence.

Source	Type	URL
ACM Digital Library	Digital Library	`http://portal.acm.org/dl.cfm`
IEEE Xplore	Digital Library	`http://ieeexplore.ieee.org/`
CiteSeerX	Digital Library	`citeseerx.ist.psu.edu`
Web of Knowledge	Digital Library	`http://wokinfo.com/`
Journal of AI Research	Journal	`http://jair.org/`
References in papers	N/A	N/A

Table A.1: Sources considered in the online search

A.2.1 Searching the online resources

Following the methodology in Oates [2005] I created groups of search terms that were synonyms or similar in meaning. The purpose of this was to exploit the possibility of using boolean search strings in modern digital libraries. The search for relevant literature is a continuous process and I went through a number of different tables of search terms. The table of search terms presented in table A.2.1 is the one I ended up using. The sparsity of the table is a conscious choice as having a general search query and then narrow the results down based on research subject proved a more effective method for finding relevant literature. The search terms were combined in the boolean search string in equation A.1

	Group 1	Group 2
Term 1	Altruism	Evolution
Term 2	Self-Sacrifice	Natural Selection
Term 3		Evolving
Term 4		Evolutionary

Table A.2: Search terms used

$$\begin{aligned} &(Altruism \vee Altruistic)\wedge \\ &\qquad (Evolution \vee NaturalSelection\ \vee Evolving \vee Evolutionary) \end{aligned} \tag{A.1}$$

ACM Digital Library

For the ACM Digital Library, the number of results on the original search query was so large that it had to be further limited by only including entries from relevant publications. Of the publications that returned matches for the query, these were included in the final search:

- Proceedings of the 9th annual conference on Genetic and evolutionary computation
- Proceedings of the fourteenth international conference on Genetic and evolutionary computation conference companion
- Proceeding of the fifteenth annual conference companion on Genetic and evolutionary computation conference companion
- Autonomous Agents and Multi-Agent Systems
- Evolutionary Computation
- Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems
- Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems - Volume 2

- Artificial Life and Robotics
- Proceedings of the 2004 international conference on Multi-Agent and Multi-Agent-Based Simulation
- Proceedings of the Twenty-Second international joint conference on Artificial Intelligence - Volume Volume Two
- Artificial Intelligence
- Autonomous Robots
- Neural Networks
- Artificial Intelligence Review

Springer Link

Springer Link allows filtering on research field, so the search was limited to Artificial Intelligence.

IEEE Xplore

The search string for IEEE Xplore was also limited to the publications

- Evolutionary Computation, IEEE Transactions on
- Computational Intelligence in Robotics and Automation, 1997. CIRA'97., Proceedings., 1997 IEEE International Symposium on
- Intelligent System and Knowledge Engineering, 2008. ISKE 2008. 3rd International Conference on

Web of Knowledge

The search on Web of Knowledge was refined to include only results from the research domains Science Technology and computer science.

Search Results

Applying the search string in A.1 to the sources in A.2 yielded the results shown in table A.2.2 In addition to exploring the vast online resources I also searched available literature in the University Library and checked reference lists in the articles I read that were of particular interest if the theme they referenced fit some of my inclusion criteria or if the title alone fit one or more of my inclusion criteria.

Source	Hits
Springer Link	39
CiteSeer	26
ACM Digital Library	25
IEEE Xplore	4
Web of Knowledge	23
Journal of AI Research	0
Other	2

Table A.3: Search results for the search string in equation A.1

A.2.2 Selection of Studies

After applying the search strategy I began selecting the studies that were relevant for my research questions. To filter the number of studies found I employed a three stage screening process where the set of found articles were gradually culled according to a set of inclusion criteria. The three stage process was:

- screening based on title
- Screening based on contents in the Abstract
- Screening based on full-text reading
- Screening based on quality

Screening based on title

The first level of screening was based on excluding articles based on the following criteria:

EQ1 *The main focus of the title is not within the field of computer science*

EQ2 *It can be quickly determined from the title that the focus of the research is neither AI nor theoretical biology related to altruism*

Abstract inclusion criteria screening

The inclusion criteria that were used for the screening based on the contents in the abstract were:

IC1 *The paper focuses mainly on evolving altruistic behavior using artificial evolution*

IC2 *The paper focuses mainly on one of the mechanisms behind the evolution of altruistic behavior in nature*

Before the full text inclusion criteria screening, the search results were as follows:

Source	Hits
Springer Link	3
CiteSeer	4
ACM Digital Library	5
IEEE Xplore	1
Web of Knowledge	5
Journal of AI Research	0
Other	2
Total	20

Table A.4: Search results after applying EQ1, EQ2, IC2 and IC2

Full text inclusion criteria screening

IC4 *The paper focuses mainly on evolving altruistic behavior using artificial evolution*

IC6 *The paper recreates one or more of the settings in which altruistic behavior evolves*

IC7 *The paper studies the genetic preconditions for the evolution of altruistic behavior*

Full text quality criteria screening

QC1 *There is a clear statement of the aim of the research*

QC2 *The Study is put into context of other studies and research*

A.3 Data Collection

Given the exploratory nature of this literature review the data collection consisted of reading the material and noting interesting points.

A.4 Dissemination

Dissemination means communicating the results, in this instance the review was handed in as part of a project.

Appendix B

Property file

B.1 Initial period

This is the property file used in Roborobo for the initial part of the experiment. All relevant changes in the final period is given earlier in the text.

```
#
# Properties for roborobo
#


# general file information

#gLogFilename =                  logs/log.txt

gAgentMaskImageFilename =        data/miniagent-mask.png
gAgentSpecsImageFilename =       data/miniagent-specs.png

gForegroundImageFilename =       data/simple\_foreground-2.png
gEnvironmentImageFilename =      data/simple\_environment-2.png
gBackgroundImageFilename =       data/simple\_background-2.png
gZoneImageFilename =             data/simple\_zones.png
gZoneCaptionPrefixFilename =     data/zonecaption

# general purpose

gRandomSeed =                    -1

gVerbose =                       false
gBatchMode =                     true

gFramesPerSecond =               60
gParallaxFactor =                1
```

```
gMaxIt =                        80000  # gen*lifeduration

# general data

gNbOfAgents =                   100

gDisplayZoneCaption =           false

gPauseMode =                    false
gInspectorMode =                false
gInspectorAgent =               false

ConfigurationLoaderObjectName = MedeaAltruismConfigurationLoader

# artificial neural net
nbLayer = 1 #should always remain to 1
nbHiddenNeurons = 5

gEvaluationTime = 400

gEnergyInit = 100
gEnergyMax = 800
gEnergyRevive = 400
gDeadTime = 1.0
gDonationThreshold = 1.1

gZoneEnergy\_maxHarvestValue = 100
gZoneEnergy\_minHarvestValue = 1.1
gZoneEnergy\_maxFullCapacity = 10
gZoneEnergy\_saturateCapacityLevel = 40
gMaxPenalizationRate = 0.5
g\_xStart\_EnergyZone = 0
g\_yStart\_EnergyZone = 212
g\_xEnd\_EnergyZone = 1023
g\_yEnd\_EnergyZone = 535

VisibleEnergyPoint = true

gEnergyMode = true
gMaxEnergyPoints = 800
gEnergyPointRadius = 10.0
gEnergyPointValue = 50.0
gEnergyPointRespawnLagMaxValue = 200 # not used here

gDynamicRespawn = true
gThresholdIncreaseRespawn =  100
gLowestBoundRespawn = 0
gHighestBoundRespawn = 25
exponentialFactor = 4

selectionScheme = pureRandom
gNbMaxGenomeSelection = 3
```

```
harvestingScheme = dynCost
fixedCost = 5
# if respawnlag>0, use non locked version.

VisibleLockedEnergyPoint = true
initLock = 0.0
iterationMax = 40

gEnergyPolar = false

#       gEnergyPointValue = 150.0


# general parameters for the self-adaptive alg. and experiment
gSwarmOnlineObsUsed = true
gDynamicSigma = true
gSigmaMin = 0.01
gProbAdd = 0.5
gProbSub = 0.5
gDynaStep = 0.35
gSigmaRef = 0.1
gSigmaMax = 0.5
gProbRef = 0.5
gProbMax = 0.5
gDriftEvaluationRate = 1.0
gInitLock = 0.0
gDriftLock = 2.0
gMaxKeyRange = 4
gDeltaKey = 2.0
gSynchronization = true



gAgentCounter =                 0
gAgentIndexFocus =              0

gScreenWidth =                  1024
gScreenHeight =                 536


gMoveStepWidth =                1
gMoveStepHeight =               1

gInspectorAgentXStart =         100
gInspectorAgentYStart =         355

# agent dynamics and structure

gMaxTranslationalSpeed =        2 # wednesday 101110 : 2
gMaxTranslationalDeltaValue =   2 # wednesday 101110 : 2
gMaxRotationalSpeed =           30
gSensorRange =                  64
```

```
gMaxSpeedOnXaxis =              2
gMaxSpeedOnYaxis =              10

gLocomotionMode =               0

gInspectAgent =                 false

SlowMotionMode =                false

gAgentRegistration =            true

gNiceRendering =                true

gDisplayMode =                  0
gFastDisplayModeSpeed =         60

gUserCommandMode =              false

# not used
gAgentWidth =                   0
gAgentHeight =                  0
gAreaWidth =                    0
gAreaHeight =                   0


# radio com network info

gRadioNetwork =                 true
gMaxRadioDistance =       32

# danger zone specific parameters (not be displayed in debug.properties)

DangerZone\_InfluenceRadius     100
DangerZone\_RobotDensityThreshold      2
DangerZone\_MaximumVelocityPenalizationFactor    0.5
```

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