A Study of Group Size and Communication in an Evolving Fuzzy-Controlled Population

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***Abstract* - This research effort is an investigation into communication activity in a distributed set of software agents. Agents exist in a predator-prey environment. Movements of prey agents are evolved upon a Mamdani type fuzzy inference system. Probabilistic predation and starvation forces, along with simulated communication activity act upon agents, causing them to cluster. Examined here is the correlation between mean cluster size after the population has sufficiently evolved, versus the average agent communication activity. Communication activity creates a loyalty to remain in a cluster for security rather than to change cluster membership. A mean r^2 correlation of 0.87 was observed with this system, thus lending credence to our hypothesis.**

I. Introduction

The field of distributed robotics has been an especially active field in recent years. Systems of distributed robots or software agents offer the promise of efficiently solving novel complex tasks in parallel either through explicit cooperation, competition or some combination thereof [8].

The absence of efficient communication abilities is a limiting factor in scalability in terms of power-consumption and wide-spread application of such distributed systems. Under certain conditions, communication has been shown to greatly improve the performance of multi-agent systems [5]. Thus efficient communication is an important current topic of research in the application of multi-agent systems to a variety of engineering tasks including distributed space exploration and search and rescue tasks. Another recent research effort from the fields of computer science, linguistics, and animal behavior is the evolution of language [1], [2], [6]. This paper combines ideas from these areas by analyzing and modeling ways group size affects communication activity in populations designed to mimic certain aspects of primate behavior. The goal is to achieve a model that reproduces results observed in nature, and analyze it for clues on insights it might provide to the realm of communication in multi-agent systems in terms of engineering applications.

In general, communication, as defined by the transfer of information, occurs in many venues in nature, including foraging, play, mating, aggression, and predation [2]. For primates in particular, communication is a reflection of our membership in a community. By making us part of a community, we reduce our risk of predation, as there are more eyes available to watch for suspect predators. Selection forces such as reciprocal altruism, where favors are exchanged between group members, help protect members of groups by warning of approaching predators and by confusing the predator with multiple potential targets. A group is defined here as a collection of agents or organisms in close proximity with each other relative to other agents. Group size is largely a balance point between the inward forces of predation and the outward forces of starvation caused by high population density at the interior of these clusters [3]. In nature, some of these overcrowding forces have been dealt with by alliance formation. An alliance is defined as a coalition maintained over time for the purpose of cooperative benefit. These alliances are maintained with various forms of social interaction such as grooming and vocal exchanges [2].

One side effect of the appearance of alliances is the need for agents to infer relationships between members, i.e. who are they allied with, and who are they not. This knowledge allows members to then manipulate and calculate in advance the potential effects that their actions might have. Thus the presence of alliances has a potential side effect of producing more cohesive groups.

One specific consequence of this hypothesis is this development of language in human ancestors. It has been conjectured that group size was pushed upward in part by an increased risk of predation as our ancestors invaded the open areas. However, at the same time, the time required for grooming in order to balance out starvation forces, was becoming excessive. Thus grooming may have in part evolved into more efficient forms of communication such as language in order to enable a further increase in group size [3].

In this research we have taken advantage of a new tool designed at the University of Washington to rapidly form a simulation that models some of the basic conditions in nature that relate to communication activity in primates. This model is used to test out this theory that as group size increases, so also does communication activity.

II. SIMULATION TOOL

This simulation has been developed using the Intelligent Controls and Communication Evolution Simulator, IC^{2}ES (pronounced Isis). IC^{2}ES is a work in progress and is built upon results and lessons learned from a previous version [7]. The simulator takes a graphical approach to simulation design, whereby users drag and connect blocks that represent some specific function. Many blocks are pre-built into the simulator, such as for example one to perform a simple genetic algorithm. However, users can very easily add their own blocks to the design tool. In addition, each block contains parameters that are specific to the block that may be edited. For example, in the case of the "Create Agents" block, an editable parameter is the number of agents to create. Users may access all editable parameters in one easily-navigable window, or by clicking on a block and editing its individual attributes. The parameter editing window for each block allows the user to alter parameters managed by the IC^{2}ES block, to view block inputs, outputs, and help information, and to change the block appearance. Source blocks such as "Constant" and "Create Environment" are available. Conversely, sink blocks, such as "Write to Cluster Plot" or "Write to Numerical Display" are available as well. This feature allows the user to quickly create and monitor data.

IC^{2}ES analyzes the block connections in the design, checking for potential errors, and forms a simulation sequence based upon the layout. To allow for feedback, in addition to normal sequential blocks, users have access to For Loops. Any block graphically placed in the interior of the For Loop is executed a number of times based on the editable parameters of the For Loop. For Loop outputs are fed back to the inputs upon each iteration of the loop. Figure 1 shows a typical loop configuration.

In addition to the design tab, another tab exists for analyzing results. For example, users can perform linear regression analysis on data to determine the goodness of a linear fit, or users can playback a sequence of images showing the population as it changes over time.

Additional tabs can also be added to allow users to customize what data they would like to view as a simulation is in the process of running. For example, multiple images displaying agent location can be displayed where the color of each agent is tied in with some other parameter such as agent fitness or communication activity. Figure 2 demonstrates this concept.

III. SIMULATION SETUP

Figure 3 shows the layout of this simulation. Despite the abundance of connections, the layout is quite straightforward. The outer For Loop cycles through rounds, intervals of which agents may be breed at. The inner for loop cycles

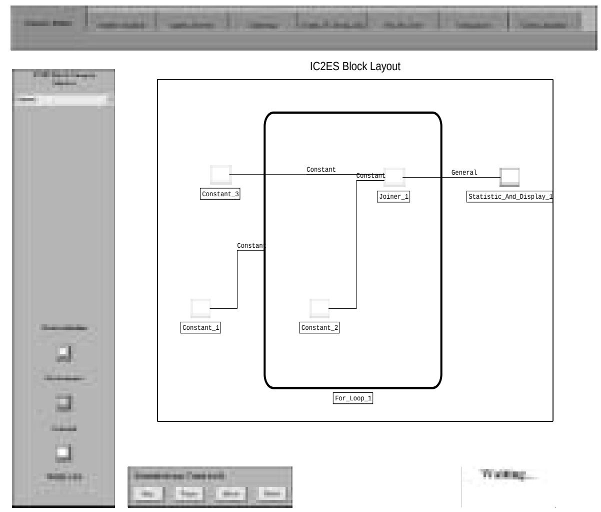

Fig. 1. A simple loop configuration in IC^{2}ES

This loop configuration simply adds together two integers upon each iteration. The output of the addition is fed back to be used as an input upon the next loop iteration. This configuration functions as a count-by-n counter.

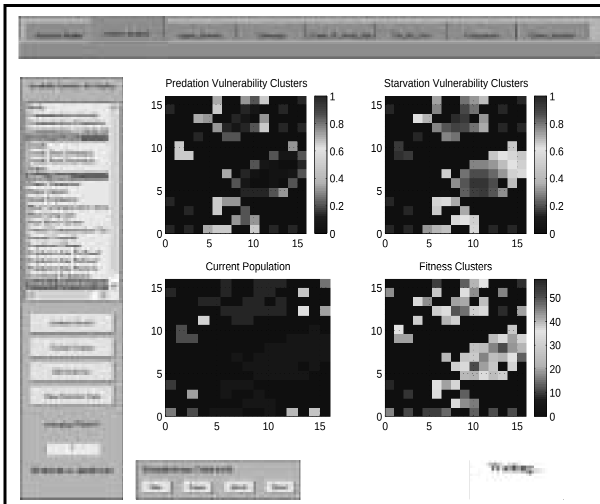

Fig. 2. Multiple images displaying agent location in IC^{2}ES

Image plots allow the user to visually observe agent population properties as they are updated throughout a simulation. For example, the plot on the lower right color scales agent fitness to allow rapid visual correlation of fitness and agent placement within clusters.

through each agent, calculating their next move based on their environment, updating their fitness level, enabling potential communication activity to take place . Initializing blocks that create the initial agents and the environment are placed outside the outer loop as one would expect.

Agents are controlled using a Mamdani fuzzy inference system. Inputs to the fuzzy inference system are normalized values of the distance to the center of the agent's cluster, the

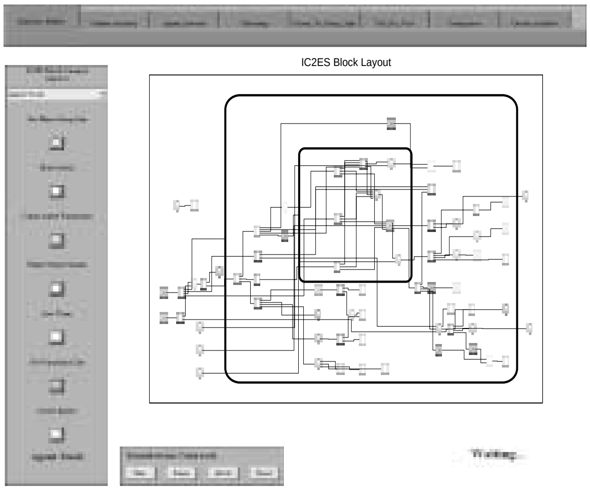

Fig. 3. Simulation connection layout in IC^{2}ES

The entire mean group size vs. communication activity simulation is dictated by the above layout. Two For Loops, one inside the other, control the overall flow by managing the agent movements.

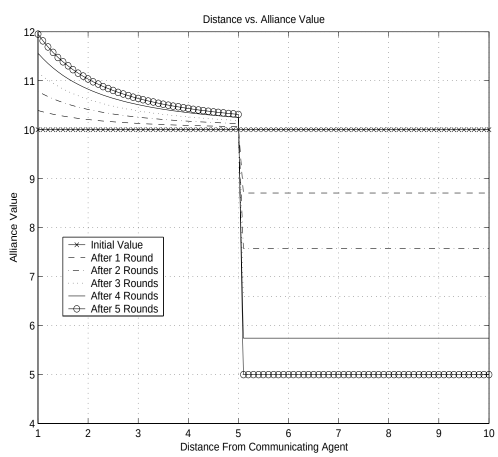

Fig. 4. Updated alliance values for agents at fixed distances from a communicating agent

For this plot Communication Distance (*CD*) is 5 and *Decay Half Life* is 5. Agents within the communication distance have reinforced alliances, while those outside the communication distance have alliances that decrease towards zero.

number of sides on which an agent is surrounded by another agent, the agent's total alliance values with other agents, and the agent's energy. The first two inputs are meant to give the agent information on its risk of starvation and its risk of predation. The third input provides it with a compact history of its communication activity. The fourth input lets the agent know how successful it has been in the past in resisting starvation.

A Mamdani fuzzy inference system was chosen over other types such as a Sugeno due to the simplicity of the model. Our fuzzy inference system uses Zadeh min-max logic, and is defuzzified by the centroid method, which in this case is in part trivial due to the discrete output behavior primitives being used. These primitives that correspond to one of the output of the fuzzy inference system are "Move Toward Cluster Center", "Move Away From Cluster", "Move Toward Cluster Edge", and "Do Nothing". Agents are assigned to be members of specific clusters based on standard hierarchal clustering algorithms.

A second output corresponds to the communication intensity with which an agent will subsequently communicate with nearby agents. Alliance values are updated using this parameter according to:

$$\begin{aligned}
&if(D_{ab} \le CD) \\
&\quad Alliance_{ab} = Alliance_{ab} + \frac{CI_a}{(3 \cdot (D_{ab}/CD) + 1)^2} \\
&else \\
&\quad Alliance_{ab} = Alliance_{ab} \cdot \frac{1}{2}^{(1/(Decay\ Half\ Life))}
\end{aligned} \tag{1}$$

where $Alliance_{ab}$ is the alliance value of agent a with agent b when updating agent a; D_{ab} is the Euclidean distance between agents a and b; CI_a is the communication intensity parameter, and is a scaling factor based on the output of agent a's fuzzy inference system; CD is the communication distance, i.e. the distance beyond which communication activity cannot occur. *Decay Half Life* is the number of moves that it would take the alliance to decay by half if the agents were to continue to fall outside of each others communication distance. Figure 4 shows typical alliance updates based on this formula.

The end results of equation (1) is that agents that are nearby to each other have alliances strengthened by the highest degree, as would be the case in primates grooming each other. Agents that are not nearby to each other, possibly in other clusters, eventually lose alliance with each other.

Alliances have another effect in negotiating conflict. If an agent wants to move to a location occupied by another agent, then the alliance between the two agents is surveyed. If the alliance meets a certain threshold standard then the movement is allowed and the agents will switch places. However, if the alliance threshold is not met, then no movement takes place.

Subsequently, agent energy is updated according to:

$$\begin{aligned}
&if\left(\left(1 - \frac{tan^{-1} Closed\ Sides_a}{tan^{-1} 3}\right) \cdot Predation\ Rate > Rand\right) \\
&\quad Energy_a = 0 \\
&else \\
&\quad Energy_a = Energy_a - \frac{(Closed\ Sides_a - 6)}{8}
\end{aligned} \tag{2}$$

where $Energy_a$ is the energy of the agent; $Closed\ Sides_a$ is the number of sides, maximum of 8, where agent a is adjoined by another agent; *Predation Rate* is a number, typically close to zero that controls the probabilistic predation risk that agents are subject to; and *Rand* is simply a random number generated with uniform distribution between zero and one. Equation (2) accounts for predation risk in the first half of the equation in which there is a small, but present risk of instant death, while the second half of the equation accounts for the effects of limited resources on energy. If an agent has less than six sides surrounded by other agents, then energy is added to the agent, otherwise it is subtracted. Agents with energy less than or equal to zero, or with energy less than or equal to forty percent that of the mean population energy are removed from the population.

Agents are chosen to breed according to:

$$\begin{aligned} \%Occupied &= \frac{Number\ of\ Agents}{Number\ of\ Grid\ Spaces} \\ \%Breed &= 8 \cdot \left(tan^{-1} 5 - tan^{-1} \frac{(1 - \%Occupied)}{0.2} \right) \\ Fitness &= Energy \cdot \frac{(Closed\ Sides + 1)}{2} \\ Breed\ Threshold &= (1 + \%Breed) \cdot E(Fitness) \end{aligned} \qquad (3)$$

Agents are breed at intervals determined by the parameter *Breed Frequency*. *Breed Frequency* is the number of times an agent will move before being given the chance to breed. An agent must have a fitness that is better than *%Breed* above the mean fitness of the population in order to breed. Fitness takes into account both the chronic effects of starvation and the instantaneous effects of predation. Also, *%Breed* increases as the environment becomes more occupied, reflecting the limited carrying capacity of the environment.

Agents which possess a fitness that exceeds the *Breed Threshold* then choose other agents to mate with based on a changeable parameter called *Breed Type*. Potential values are proximity (choose the nearest agent), random (choose randomly), and fitness (choose the non-mated agent with the highest fitness). To encourage cluster formation, proximity mating was typically used in the simulations presented in this paper.

Standard crossover operations, with multiple crossover points, are then performed on the mating agents' chromosomes. Chromosomes consists of the means and variances of the membership functions of the fuzzy inference system, as well as the output rules

The resulting chromosomes are then mutated with a decaying mutation rate. The resulting new agent that possesses the new chromosome is given alliance values that are an average to that of its parents. The new agents initial energy is likewise an average of that of its parents. Placement of the new agent takes place as close to one or more of the parents as possible.

The simulation continues in this way for a preset number of rounds or until the population becomes extinct or oversaturates the environment. Typically, the modulation of the *Breed Percentage* and other factors allows for an equilibrium occupancy of the environment. Typical experiments have resulted in equilibrium occupancy values of between twenty and fifty percent.

Throughout the simulation run, results are ported to appropriate plots and numerical displays for subsequent analysis.

IV. Simulation Results

Twenty-five simulations were run, with variations in many setup parameters. For example, the initial number of agents was varied between an initial occupancy of 10% and 50%. Parameters were varied in order to demonstrate the robustness of the linear relationship between group size and communication activity.

Figure 5 shows the percent occupancy of the environment by simulation agents over simulation time. In most simulations there is a dip in percent occupancy at the beginning as non-fit agents created during the random initial setup are culled primarily by predation forces. Subsequently, the percent occupancy rises to an equilibrium level around which it oscillates. In Figure 5, the equilibrium level was approximately 24%. Figure 6 demonstrates similar behavior in the mean group size as a simulation proceeds.

As expected, the breed threshold is modulated according to the percent occupancy of the environment. Figure 7 shows this principle. During the initial dip in percent occupancy, the breed threshold decreases to allow more agents to breed, thus preventing extinction, and allowing the agents to

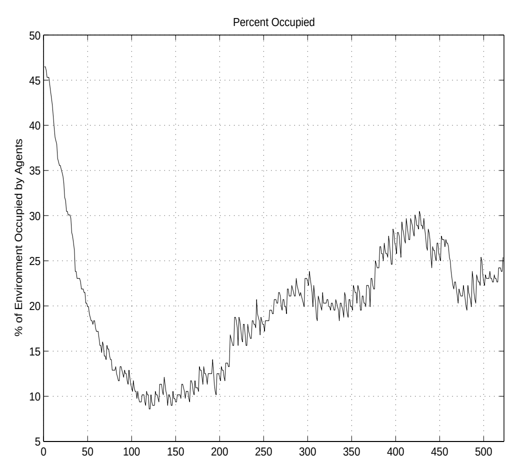

Fig. 5. Change in environment occupancy by agents

From round number zero to about 125, the population decreases rapidly as unfit agents with randomly initialized chromosomes are selected out. From round number 125 to 300 the population rebounds, followed by a period of small oscillations around an occupancy equilibrium.

recover to the carrying capacity of the environment. Minimum fitness is displayed to help track when starvations occur. Deaths due to starvation are in fact rare compared to predation-related deaths in most of the simulations that have been run. Approximately, 30 times as many predation deaths occur than starvation deaths. One potential cause would be a small distribution of fitness values across the population. In this case fitness is not able to decrease below a fixed percentage of the population mean fitness because most fitness values are crowded around the mean.

Behavior primitives were often observed to quickly reach equilibrium values in the population. Figure 8 shows the frequency of the four behavior primitives over the population at the end of each round if one were to assume the environment would remain constant before each agent moved. This assumption is of course false, however, the concept is still useful for judging the success of behaviors. The "Away" behavior often was observed to die out quickly. Predators that often moved away from clusters would be at a greater predation risk, which often outweighs the benefits of escaping from potential starvation. If the simulation were changed to one in which agents were periodically removed from their environment and placed into new ones, then it is believed that the "Away" primitive would be of greater use.

We found a mean r^2 value for a linear fit to the data of 0.87, with a standard deviation of 0.069. Typical Results are displayed in Figure 9. This result means of course that 87% of the relationship between average group size and communication activity can be explained by the linear fit, while the other 13% is potentially random noise. The evolving nature of the population clearly introduces a random element into this simulation, thus 0.87 is sufficient to back our original hypothesis, although further research would be desirable to test fully what circumstances this result was valid under. The mean slope of the best-fit line, normalized for the number of rounds, is 8.9, with a standard deviation of 2.53.

It is interesting to note that in earlier experiments, where communication amplitude was not evolved, an even higher linear fit was discovered. The mean r^2 value in this case was found to be approximately 0.96. However, in not allowing communication amplitude to vary, the two variables are designed in such a way that correlation is inevitable, therefore it is not surprising that we found a higher r^2 value.

There are a number of reasons that may potentially explain why mean group size was found to be highly correlated with communication activity. For example, communication activity may indicate to an agent how successful the cluster it is in has been. If the agent has high alliances with nearby agents, then most likely the agents in this cluster have been working together for a significant period of time. Thus the evolved interactions of these agents may be successfully countering the ever present starvation and predation forces. It would then be to the advantage of the agents present in that cluster to stay within the successful cluster rather than to leave it for an uncertain environment.

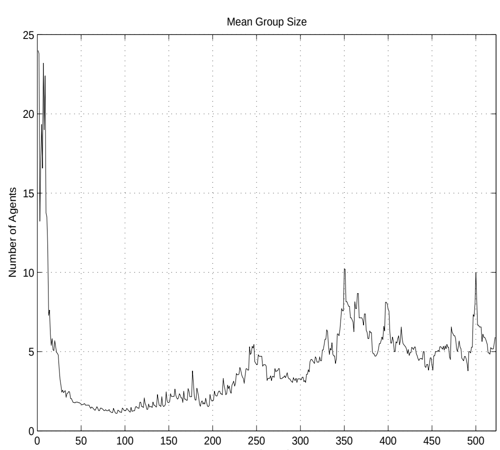

Fig. 6. Mean group size

Mean group size decreases rapidly as the initial population is winnowed based on agent fitness. Mean group size starts to increase at around round number 100. However, the overall occupancy remains fairly constant until round 150. The clustering of agents during the period between rounds 100 and 150 enables the subsequent rapid growth in percent occupancy. The final equilibrium mean group size is approximately 6 agents.

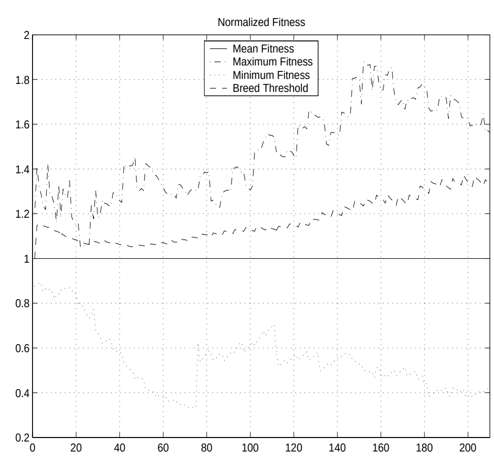

Fig. 7. Relative population fitness values

Much of the high-frequency oscillations observed here are caused by the frequency of breeding, which in this case is every five rounds. At round 75 an agent is removed due to starvation, as the minimum fitness suddenly changes. At all times except between rounds 22 and 28 the agent with the maximum fitness in the population has a fitness that is above the breeding threshold, thus at least one agent in the population will breed.

V. Conclusion and Future Work

In this simulation we have demonstrated the goodness of a linear fit to the relationship between mean group size and communication activity. An r^2 value of 0.87 was found for the correlation of these two variables over a number of experiments with a variety of parameters adjusted, thus providing a certain robustness to the result.

In the future, we will adapt this simulation from a software environment to a hardware environment. A hardware implementation will more easily allow the agents to free themselves from a discrete grid system. Using multiple Khepera robots, agents will communicate with one another with Infra-Red transmitters and receivers. Cluster information will be extracted from observations of the robots' immediate environment. We hope to reproduce the results generated here in the software simulation and remark on any differences that may arise due to issues related to the physical implementation of this simulation. In addition, more in depth mathematical modelling, as in [4], with be performed in order to improve the closeness to reality of the simulation model.

Acknowledgements

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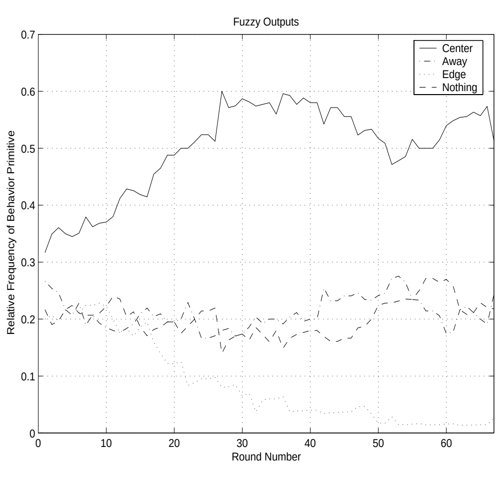

Fig. 8. Frequency of behavior primitives

The behavior primitives are outputted from each agent's fuzzy inference system and accumulated in this plot for each round. In this simulation agents adapted a strategy of mostly trying to move toward their cluster center, while also occasionally moving away from the cluster or doing nothing. Agents that moved toward their cluster edge appear to be at a disadvantage to other agents, due in part to increased predation forces at the cluster edge compared to the interior.

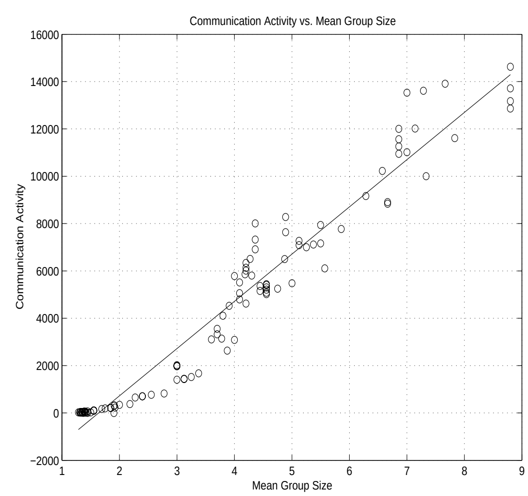

Fig. 9. Typical linear fit between mean group size and communication activity

In this simulation, cluster sizes ranged from a single agent up to a maximum of 28 agents. Data points are taken after each round. However, only rounds after which the population had reached a percent occupancy equilibrium were used in the plot above so as to discount the transient effects caused by the high genetic variance in the initial non-culled population.