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On Agent Communication in Large Groups

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1 Introduction

The problem is fundamental and natural, yet deep — to *simulate* the simplest possible form of communication that can occur within a *large* multi-agent system. It would be prohibitive to try and survey all of the research on “communication” in general so we must restrict our focus. We will devote our efforts to synthetic communication occurring within large groups. In particular, we would like to discover a model for communication that will serve as an abstract model, a prototype, for simulating communication within large groups of *biological* organisms.¹

The primary and immediate application of research on group communication, currently being actively pursued by the military, is finding a robust solution to the problem of communication within systems or swarms of remotely located agents e.g., mobile, autonomous, interacting robots.

On the commercial side, the driving application is the communication of *processes* — groups of autonomous programs operating in a distributed environment i.e., the knowbots of data mining, or the electronic agents entering into on-line, real-time buying and selling auctions. A recent special section in the Communications of the ACM [34] attests to the timeliness and importance of the subject of electronic agents inhabiting the internet.

We should remark at the outset that group communication must incorporate stochastic elements in order to be biologically realistic. Surely useful models will acknowledge noise affecting both receivers and signalers as well as background noise within the environment. This has potential practical implications as well. One theory underlying autism suggests that it is due in part to the inability of the brain — a large communicating system of neuronal processes — to filter out the signal from the background environmental noise in a “normal” manner.

Finally, there is another stellar application, less obvious perhaps than the previous ones, but still having significant financial impact. It is research on creating communicating populations of lifelike agents with *emotion* for use in the entertainment industry [4] [31]. Imagine the revolution that will

¹Evidently we are distinguishing between biological and non-biological communication. Therefore we should try to make clear what we mean by non-biological communication. Usually, we mean electronic communication, wherein the efficiency and effectiveness of the communication are the key considerations, not the mechanisms and principles which underly it. An example of non-biological communication is the electronic communication *network*. We also remark that we will try to avoid discussing the question of evolution of *language*, which seems to be a wholly separate endeavor from that of identifying and elucidating the evolved *behaviors* we associate with primitive communication.

occur when an interactive theater populated with virtual agents (avatars), or an art installation featuring groups of “creatures” that one can create, control, and directly communicate with [41], becomes routinely available.

The most comprehensive treatise on the subject of the biological evolution of animal communication is Hauser’s book, *The Evolution of Communication* [16]. Though Hauser provides many insights, it is easy to conclude that after four billion years, evolution has evolved living organisms of such complexity that our ability to locate, distinguish, or identify the most primitive biological organisms capable of communication has been obscured. Similarly, ethology has not advanced to the point where it is possible to meld observed behavioral characteristics into a synthesized “basic” model of the communicating organism.

Thus we must turn to simulation. The kind of simulation we are striving to achieve is the kind of simulation understood by the nascent discipline of Artificial Life (Alife). In Alife, a population of synthetic, computer-modeled organisms — the agents — is instantiated in order to perform evolution experiments in the hope of revealing the emergent properties of life itself, or as it is often stated, life-as-it-could-be instead of life-as-we-know-it. On one hand we believe that Alife can supply evidence confirming how biological communication evolved or emerged, and on the other hand we expect that Alife experiments can establish the viability of proposed models of biological communication.

The difficulties of approaching group communication problems from the Alife perspective are overwhelming. In the late twentieth century, science is nowhere close to being able to convincingly simulate large *groups* of digital organisms. At best, we can convincingly simulate the crude abstraction of *one* organism. In this report, we will undertake to examine how such abstractions might be modeled, what cues from the research biology literature we can obtain in helping us to construct group models, what we might learn from them, and how we should proceed in the quest toward further developing them.

This report is organized as follows. In section two we introduce the digital organism. In section three we consider digital species. In section four we survey some of the Alife literature on group communication. In section five we try to obtain clues from relevant biological findings. In section six we speculate about a mathematical model. In the last three sections we present the key contributions we have to offer: an initial design, a discussion of an implementation done by an honor’s thesis student, J. Crawford, and an analysis of how the design might be advanced.

2 What is a Digital Organism?

Since there is no general agreement as to what constitutes a digital organism, we can only review some of the models that have been proposed for digital organisms. As a computational entity, a digital organism will be understood by the “brain” it uses. Since we deal in abstract models, any so-called brain is only a first-order attempt to approximate or mimic the *functionality* of a living brain, not its chemical processes. With this understanding, there are several models to discuss.

2.1 Decision Tables

A decision table is the simplest and most obvious model of a brain. A decision table is a look-up table that can be used to specify a set of conditions that must be satisfied to trigger an agent to signal, and what that signal will be. Similarly a decision table can specify the response of an agent upon receipt of one or more signals.

2.2 Finite State Machines

A finite state machine requires each agent to occupy a “current state” and to associate a transition table (i.e., decision table) with each possible state. Besides performing actions as described above, the associated decision table must also control state changes. A finite state machine is well-suited to an agent that will function solely on a stimulus-response basis.

2.3 Rule Production Systems

Effectively, a brain patterned after a rule production system would consist of a grammar. An action by the agent would be the behavior obtained as the result of a derivation using the rules of the grammar. The sensory inputs, together with internal states, would specify the set of non-terminals that are currently “active” and can therefore be used in the derivation. It is not easy to see how to make this technique computationally effective. The appeal of rule production systems, however, is the compact form they may assume, the logical consistency they provide for generating behaviors, and the potentially interesting mating algorithms (genetics) that one can contemplate designing for them.

2.4 Petri Nets

Petri nets are a primitive form of neural nets which will be discussed shortly. Petri nets have been used in a wide variety of applications in computer science. We refer the reader to most any discrete mathematics text for a precise definition and detailed exposition of their use. Though they have not seen widespread use as the basis for digital organisms, they are perhaps an untapped resource, since they offer significant advantages for designing organisms to respond interactively in a *temporal* environment [33].

2.5 Artificial Neural Nets

Neural nets are the preferred artificial intelligence model of the human brain. They have formed the basis for digital organisms in countless Alife settings. It would be futile to try and reference even a representative set of examples. In general, we find that the many flavors of neural nets adopted for various Alife simulations *underperform* their expectations. It seems that using a minimal digital neural net provides insufficient processing capability for synthesizing the living neural net. Therefore it is arguable that the neural net is the best structure to adopt when designing the simplest synthetic communicating organisms. Dyer [10] comments about the intense debate over the shortcomings of adopting neural nets in Alife simulations, and even questions their place within the biological evolutionary development of animal intelligence.

2.6 Directed Graphs

Directed graphs have been shown to be particularly useful in exploiting the genotype-phenotype relationship when evolving highly complex, adaptive digital organisms [40] [44]. Directed graphs make it relatively easy to develop mating algorithms, and can serve as blueprints for instantiating creatures with sophisticated sensory and locomotive features. Since directed graphs tend to emphasize the physical characteristics of the digital organism, we are unsure how they should be treated with respect to designing the “brains” of primitive digital organisms. Perhaps they can best serve as a template for designing the more sophisticated *sensory* systems that will be required for effective synthesized communication.

2.7 S-expressions

In the Genetic Programming of Koza [26], S-expressions are executable, functional programs implemented via expression trees. The leaves of the trees, the inputs and constants to the program, are chosen from a terminal set, while the internal nodes are chosen from a set of processing functions. Evaluation of an S-expression yields a prospective “solution” which we prefer to think of as a behavior. Once a metric is imposed on the space of prospective solutions, (i.e., fitness is defined) mating and evolution of a population of S-expressions is straight forward. Two S-expressions are mated by simply swapping sub-structures. Impressive results using this paradigm have been achieved for certain *optimization* problems. We shall discuss one Alife application. Haynes and Sen [17] used S-expressions to co-evolve cooperation strategies for a predator-prey game. The objective in their game was for four predators to surround one prey. All agents moved orthogonally on a toroidal grid. Unfortunately, their predators were not capable of signaling to one another. Haynes and Sen found that their prey was more successful at evolving escape strategies than their predators were at evolving capture strategies. Thus Haynes and Sen concluded, as have many researchers before them, that Genetic Programming using S-expressions is wholly dependent upon the encoding of the problem that is used. Only when the terminal sets and function sets are carefully designed will success at finding solutions result. In other words, one’s success using S-expressions derives from one’s skill in designing a special purpose, domain specific language to solve the problem at hand. Thus it appears that S-expressions make it difficult to model an adaptive, general purpose brain for a digital organism.

2.8 Independently Executing Processes

Mutable, independently executing processes that model digital organisms are more fiction than fact. There do not exist sufficiently flexible *general purpose* programming languages that will support the mating requirements needed in order to evolve populations of sophisticated procedural programs. The pioneering work done by Ray [36] uses a toy language to investigate self-reproduction, speciation, and evolution. This initial work has been successfully duplicated, with variations, by others. But subsequent work seems to be focused on the evolution of more complex “multicellular” digital organisms as opposed to primitive organisms with either communication or cooperation capabilities [37].

Our brief overview of digital organisms exhibits the range of possibilities as well as some of their shortcomings. To proceed, we must address the nature of the communication we envision, for it is one thing to study communication in the context of a predator and its prey, and quite another to study communication in the context of signaling the presence of prey or of food to a *group* of one's own kind. Surprisingly, this brings up a question that is often glossed over in the Alife literature: How are digital organisms classified as being in the same species?

3 What is a Digital Species?

There is no litmus test for describing a biological species. A paper by Paterson [35] neatly sidesteps the issue using two assertions. First, Paterson remarks on the origins of a species:

... it is evidently in small populations that speciation occurs.

and then he comments on the persistence of a species:

Once evolved, a species is stabilized for several reasons, viz: (a) its restriction to a habitat similar to the one in which it evolved — this factor keeps many adaptive characters under stabilizing selection; (b) the coadaptation of males and females for the signaling characters of the SMRS (Specific Mate Recognition System); and (c) the size of the population, after it has grown as a result of its release from directional selection.

The first claim is noteworthy because it effectively defines a species in terms of a *mating* population, and the second is useful because it recognizes the importance of communication to a species through some signaling system. But there is still room for confusion because Paterson's micro-populations would appear to do a better job of capturing the notion of a *deme*, the reproductive community of an individual, rather than characterizing a group of individuals comprising a species.

It will be to our advantage to adopt the convention that limitations induced by genetics — who or what can mate with whom — will suffice to define a species. This is often treated in a cavalier manner in Alife research because too often mating limitations are fuzzy. There is a propensity to allow digital entities to mate freely. Mating therefore is an instance of simply exchanging genetic material, more reminiscent of viruses and bacteria

swapping fragments of DNA than *organisms* that mate, grow, learn, and communicate as a group!

4 Previous Alife Efforts

Our starting point is Dyer's comprehensive, ground breaking review of animal intelligence and the early artificial life efforts to synthesize intelligence [10]. His exhaustive list of references serves as a remarkable entry into the biological sciences literature, and his review of the first efforts by MacLennan [30] and Werner and Dyer [48] are cogent. But Dyer pays scant attention to *group* communication. We shall give a more complete survey of Alife developments in this area.

Hogeweg [19] modeled group communication as *pairwise* "interactions" between *initially* identical individuals as part of her investigation about emerging social structures. The intent of her model was to imitate a swarm of bumble bees. Because she placed dominance interactions in the center, and provided a neutral periphery, the key to her model was her swarm's spatial organization. The most dominant agent occupied the center with weaker agents radiating out to the periphery. Thus, for Hogeweg, group communication was translated into questions about spatial positioning.

In [19] Hogeweg offered yet another species communication simulation, which was significant because it employed several stark assumptions. In particular, there was an assumption that her agents, called SKINNIES, were inherently "social." Thus when no other SKINNY was close enough, a SKINNY would move towards the nearest (group of) SKINNIES. This set up a tension between SKINNIES. When they edged too close to one another a dominance interaction had to take place. From Hogeweg we learn about the importance of the byplay between a group's spatial organization and a group's communication potential. It would be of tremendous value to further clarify the relationship between the emergence of communication and the emergence of *group formation*.

De Bourcier and Wheeler [9] consider the problem of false signaling. Why should an agent signal the presence of either food or a predator in the first place? Can an agent deceive another agent into fleeing by issuing a warning call? It is suggested that one consequence of false signaling is that receivers must use additional cues to decide if the signal is correct. Some of the most recent Alife research suggests that large groups provide a deterrent to false

signaling.² It is possible that the risks of punishment by the group for being exposed as a false signaler outweigh the gains of successfully false signaling. It is as though individuals within groups are addressing the “exploitation versus exploration” dilemma: If sure then exploit (false signal); if unsure then explore (honest signal).

Werner and Todd [49] investigate the hypothesis of an arms race for *variation* taking place within the confines of the signal itself. In their simulation, diversity of song emerges through females rewarding those males who are able to surprise them by introducing (aesthetic) differences and new improvements upon established songs. The significance of this is that it has a bearing on what constitutes the nature of “signaling.” Werner and Todd fail to provide biological evidence to motivate their work even though it exists. Hauser [16, page 373] cites experiments by Ryan and Ryan who contend that in certain bird species, females exhibit preferences for traits that do not yet exist in males, and therefore males have the opportunity to evolve advertisement calls that more directly tap into the female’s sensory biases.

Holland et al [20] offer an intriguing idea regarding communication and synchronization. Much of group communication seems to be about synchronization, and the idea put forth by these researchers is that the frequency with which an individual agent is required to participate (signal) provides information about how many agent participants there are.

For biologists, it might be easy to overlook the role the *environment* plays in communication, but to the Alife community the requirement that the environment be synthesized for the organisms has necessarily led to the discovery that it too can play a major role. In fact, it has led to the notion of environment based communication — communication that requires no intra-agent communication whatsoever. The environment is the computing medium! Todd and Yanco [45] in software, and Beckers et al [5] in hardware, are able to simulate evolved group behaviors using this paradigm.

The fragmentary data we have reported upon reveal that there is no concentrated effort to develop from first principles a simple model underlying group communication. As we shall see, this may be due in large part to the confusing and conflicting ethological data.

²Note that failure to signal can also constitute a form of false signaling.

5 What Can We Learn From Biology?

After spending time researching the literature, it becomes relatively easy to select a species together with a field study that will help support almost any hypothesis. Perhaps nature is overevolved, making it impossible to tease out fundamental principles through simple observation. Reading about primate copulation calls [16, page 406] furnishes a good example. We invite the reader to formulate a hypothesis for why such calls are made and then consult [16] in order to identify a primate species and a companion study supporting his or her hypothesis. The situation is discouraging. With this caveat, we will look at some of the findings of biologists. They are disparate and difficult to organize. They will complicate our task. However, they will lend support to some of the decisions we will make when we attempt to design our communication simulation.

Ethologists argue in many instances in favor of *simple* rule based behavior. In fact, Hauser [16, page 590] gives a five-step decision *algorithm* to explain the plover's behavior in the presence of a predator.³ This we find encouraging. We seek evidence that biologists find algorithms to be an acceptable way to model behavior.

We would like to learn as much as possible about what the nature of the most primitive sensory *input* should be. This question does not have as clear cut an answer as we would like. MacDougall-Shackleton and Hulse [29] provide convincing evidence that starlings have *concurrent* perception of both absolute and relative pitch, and that they can *choose* to process on an absolute or relative basis. Evidently sensory input is not simple.

An important issue that has been extensively studied is the emergence of the semantics of the signal. This is intertwined with the *social* structure of the group. One might expect that the sharing of individual interactions evolves into group dynamics. Hausberger et al [15] found that for starlings the pattern of song sharing reflected the social organization. But they also concluded that vocal plasticity accounted for the wide variety of possible social situations in this species. This is unsettling. It makes it difficult to divorce the issue on one-on-one agent communication from group communication, but on the positive side, it is a wonderful argument in support of ensuring that there is a stochastic element involved in the receiver's ability to correctly analyze any signal.

³It is interesting to note that the swarm simulations of situated, independent, autonomous robotics appeal to elementary decision algorithms that seem to fit this category nicely.

We would like to hypothesize a large group relying on one underlying signal. But this may not be realistic. For example, there is evidence that it may not be feasible to hypothesize one *vocal* signal. Kaltwasser [24] proposes a minimum of ten sounds used by black rats. Some sounds are associated with several behaviors (a context-sensitive language) and some behaviors are associated with several sounds (an ambiguous language). In an abstract model, how many signals are too few? How many behaviors are too many?

In [16, page 54] we find evidence concerning how the nature of the signal is tied to the nature of its semantics. Specifically, it is mentioned that in avian mob calls, whose purpose is to recruit group members to help drive a predator away, the call is optimized with respect to *localizability*, but with warning calls, whose purpose is to alert group members to danger *without* alerting the predator, the objective is to emit a non-localized sound so the predator cannot locate the warning bird. This shows that models which map behaviors to signals indiscriminately are missing out on a rich byplay between signal and behavior.

Most researchers in the biological sciences would formulate our communication problem as communication of one *species* using one sensory *system* e.g., auditory, olfactory, or visual. But there is an additional complication. Should the *simplest* biological signaler-receiver system posit *different* reception mechanisms for signaler and receiver? In anurans, males sing and females move about within the calling arena to find an appropriate mate. Since males alternately rest and sing it is proposed [16, page 118] that males receive the signals of other males with the intent of determining the optimal time to initiate a signal, while females receive signals for the sole purpose of assessing the quality of the signaler.

We believe that some form of *memory* is a principal ingredient profoundly affecting the signaler-receiver system. What is the exact nature of such memory? As in [16, pages 283–287], we consider nightingales because of their immense song repertoire. We shall take up the problem of time constraints on receivers shortly, but for now we consider the nightingale’s feature of *learning* from tutors through repetition. Can such training be ignored in a simulation? It has been observed, somewhat casually we think, that signals can change during the course of an agent’s lifetime. To the best of our knowledge, this subject has been dealt with by the Alife community only within the context of acquiring language, not within the context of *learning* semantics.

There is a degree of parallelism — agents act simultaneously — in group communication that imposes inherent difficulties on modeling and studying

it. McGregor and Dabelsteen [32] give an excellent rationale for why a clearly defined model of a group of signalers communicating (long range) to a group of receivers is necessary. They consider many subtle aspects of simultaneity, mostly from the point of view of birds and their songs, including:

- directing and restricting signals
- eavesdropping
- implications of alarms

Their critical observation is that this area is murky from a biological point of view because of the difficulty of obtaining simultaneous measurements of individuals, and murky from the mathematical point of view because of the intractability of working with multiple signalers and receivers. This argues for the Alife approach, but against its success.

What factors are we to consider then when we are thinking about individuals? Stacier et al [42] address the topic of group communication in the dawn chorus from the individual's point of view. Through *observation*, they attempt to reinforce some of the views of McGregor and Dabelsteen. The following intriguing excerpts underscore this:

- “Dawn singing appears to be socially contagious.”
- “Dawn singing is often directed at particular neighbors.”
- “During pauses, males turn their heads from side to side as if intently listening to neighbors’ songs and appear to respond to particular neighbors (e.g., by matching song types and cadence).”

They also support the algorithmic approach by suggesting that “dynamic programming provides a way to calculate how conflicting needs can be optimally balanced in daily routines, and, overall, the integration of mathematical modeling and observations of natural singing behavior appears to be a promising approach toward explaining the dawn chorus.”⁴

Noise becomes an experimental hindrance when studying group communication in the field, so it is useful to be able to quote from Gerhardt and Klump [12] who are able to obtain evidence that for green tree frogs, “the calls of only three to five males would equal the background noise at the

⁴Here, dynamic programming [22] refers to a static simulation which simulates an optimal daily routine for an arbitrary agent by calculating the optimal choice of behavior at each time step that such an agent would need to achieve certain goals.

female’s position” and therefore “a female can assess only a small fraction of males in a large chorus at any one position.” This is marvelous support in favor of incorporating locality into an agent group.

The old adage that “timing is everything” appears to play a pivotal role in group communication. Biologists supply us with some remarkable data. In frogs, according to Tuttle et al [46], “entire choruses can shut down within a second of the time that a fringe-lipped bat or a fringe-lipped bat model arrives at the edge of their pond.” We will be inspired by this fact when it is time to design a communication *task* for our group of synthetic agents.

Since we feel timing and memory constraints have not been adequately dealt with in Alife software simulations, we appeal to a passage from Hauser, discussing songbirds, which we find illuminating [16, pages 285–286]:

Last, when individuals were tutored with songs produced at either a normal rate of delivery (i.e., 4 sec. between successive songs), dense (i.e., 1 sec. between successive songs), or spaced (i.e., 10 sec. between successive songs), subsequent performances indicated that individuals were under capacity and time constraints . . . The latter results suggest that as soon as the memory system begins registering incoming sound, there is a time window that parses the incoming stream of information, and this allows for the segmentation of song types into song packages.

Hauser also notes [16, page 339], “One study of 3-day-old infants suggests that timing events can provide at least some relevant cues to word boundaries.” Considered as a whole, such facts, help motivate the introduction of “timers” into agents during simulation.

6 Where is the Mathematical Model?

To date, progress towards developing a mathematical model for large groups of agents has taken place only in the conventional arena of continuous models, which considers populations of agents not individuals. Perhaps there is some convergence taking place. Stevens [43] examines aggregation by *approximating* lattice based exchange of diffusing and nondiffusing “signals” by continuous ones. Lewis [28] proposes a set of equations for nonlinear stochastic invasion which reveal that the impact of the spatial correlations among *individuals* make density dependent effects significant. Such preliminary work suggests that the long standing continuous approach of modeling

populations as single entities without modeling the individuals themselves may be giving way to the Alife approach of modeling populations only by modeling individuals and then observing their interactions.

7 What Should the Initial Design Be?

We have identified some of the criteria that need to be addressed in order to get a simulation of communication within a large group of agents off the ground. They include:

- How many sensory systems should the agents have?
- How many signals should the agent's sensory system admit?
- Do the agents learn signals, inherit knowledge of signals, or some combination of both?
- What strategy do the agents use for signaling and receiving?
- Why are the agents communicating?
- What is the biological motivation for the agents?
- Are the agents mobile?
- How many agents form a large group?

In simulation, not all of these criteria can be managed at once. Consider mobility. If agents are mobile, there are two thorny issues to be dealt with simultaneously: (1) Does the motion make sense?, and (2) Does the communication enhance, support, or interfere with the motion? Similarly, consider multiple sensory systems. The problem of *integrating* two systems seems daunting. Following Alife methodology we would like this integration to arise as an emergent property. But we are not far enough along the path toward "guiding" emergence in an Alife simulation to be able to arrange for this to happen per force.

Thus we begin with one group, immobile, and communicating using one sensory modality. In nature is there such a group? Some biological candidates representing the agents we would like to synthesize are easily rejected e.g., prairie dogs use too many senses, dolphins must be mobile, sea anemones don't communicate with each other, instead they react with the environment, etc. There is no perfect model to guide us. But let us consider

a *roosting* flock of birds. Such a group is immobile and has one primary sensory system, avian calling. Note that this example will also serve to guide us when deciding the group’s size as well.

How are we to justify one sensory modality, sound, as the *only* form of communication? Clearly, roosting birds can communicate visually. If we were to assume they are in darkness then they cannot communicate visually, but in that case they would normally be silent. Fortunately, there is a phenomenon that does give rise to *sightless* calling in many groups of avians, the dawn or dusk chorus. The dawn chorus has been more often studied. A major effort by Staicer et al [42] suggests several reasons *why* birds might call during the dawn chorus, but there is no consensus on the matter. Fortunately for us, none of the hypotheses seem to depend on the fact that birds have a potentially unlimited supply of different calls (signals) they can make.

We mentioned previously the little known efforts of Hutchinson et al [22] to use dynamic programming to help explain individual bird behavior in the dawn chorus. We do not consider this work to be an Alife simulation because the agents are neither evolved nor autonomous, nor do they interact asynchronously. Thus our model will represent an entirely new and different approach.

In order to proceed, we will have to make some further simplifying assumptions. We are unable to cite from the literature, so we will rely on personal observation. We will assume that at *dusk* a roosting flock of birds settling down for the night will chorus in a chaotic (i.e., unsynchronized) manner. We assume for our model that even though there is a “wall” of sound the birds, like the green tree frogs, can communicate (signal and respond) directly with only a few others of their kind. This critical assumption will allow us to explore more interesting scenarios than that of one agent simply calling to, addressing, or admonishing the entire group. We make no assumptions about the spatial locations of individual birds within a flock, nor the precise reason for why roosting birds chorus. It seems reasonable to hypothesize that they are comforting or reassuring each other. That is, they are purposefully trying to maintain a background comfort level of sound. We are uncertain, in advance of experimentation, whether or not this overall sound is compartmentalized⁵ i.e., an amalgam of sounds from independent subgroups.

⁵It seems obscure, but a passage by Cole [7] suggests an intriguing but more far-fetched possibility to us. The passage is:

Still we are a long way from *group* communication. We would like our model to permit us to be able to *propagate* messages of *content*. Again we fall back on personal observation. If an intruder approaches a roosting flock, which is behaving in the manner described above, the flock swiftly quiets. We do not believe there is one alarm cry made that is heard by all. We do not believe an alarm call is being relayed. We do not believe that all birds can directly sense the intruder. This question concerning what *mechanism* is involved in the quieting of the flock appears not to have been considered in the literature nor, unfortunately, to have been asked for the frogs that can quiet as a group in one second! The effect we are describing is familiar to everyone. Imagine being in a noisy classroom. A teacher standing at the front of the room tells the class to be quiet. The class as a group doesn't hear, but after the first few rows of students, who do hear, become quiet and *remain* quiet, the silence *propagates* and eventually the entire class quiets. This motivates a fundamental feature of our design; namely, that each agent is *always* signaling, because we consider silence itself to qualify as a signal.

What signal processing *strategies* might the roosting birds we are envisioning be using? In 1996, a University of Richmond senior, Jessica Crawford, undertook an implementation based on the above design as an honor's thesis project [8] in order to conduct experiments exploring strategies that agents could adopt for achieving various group tasks. Before discussing her findings, we wish to remind the reader once more that there is an application for this research that we are particularly interested in. That application is the design of automated group behavior for virtual populations. One can consider a virtual crowd in a feature film that would hush "properly" at a director's command, or consider as a plug-in component to the "behavior engine" of a computer game, virtual populations that could vocally communicate with one another and then respond appropriately.⁶

Fractal time occurs when the distribution of events is self-similar on a temporal scale; that is, if we measure the pattern of events with equal relative precision over many time intervals, it is the same regardless of the scale of measurement.

One might interpret this as suggesting that the group chorus effect can occur, and can be regulated, by having each agent try to call so as to perceive the world in the same way.

⁶As this is being written an animated feature film, *ANTZ*, is being completed that does incorporate, on a very limited basis, some of these ideas. The group size is impressive, but the truth is that significant scripting of individual agents is required in order to accomplish the group tasks shown in the film.

8 Crawford's Cacophony Simulation

We begin by reminding the reader that we often view communication as a form of synchronization. Hence we are led to formulating group communication tasks as problems about discovering the strategies, or rule systems, agents need to follow in order for synchronization to occur. We recognize that such synchronization needs to take place in a cluttered (noisy) and clustered (busy) environment. We are now ready to describe in detail the Crawford simulation.

Agents were placed in a stationary cluster on a two dimensional grid. Each agent was an asynchronous, autonomous process (thread) that was able to emit a sound. Sounds were selected from a finite set of volume emission levels. Also selected were time intervals for the duration of the sounds. Agents would issue their sounds and then put themselves to sleep for their sound duration intervals. Upon reawakening, an individual agent could sense the current background volume level, as well as the volume emission levels of neighbors within a fixed distance, and then use this data to repeat the cycle.

The first stage was to implement a group of agents *maintaining* a proscribed background auditory level. This was later to be used as the status quo, all-clear state for the group. The global sensory input variable was the group's volume, which was calculated by averaging each agent's volume contribution. The stationary group of the simulation was initially formed by randomly distributing agents based on polar coordinates so that there were more agents at the center than at the periphery. Simulation parameters were the number of agents and the minimum and maximum times an agent could emit a sound for. These extrema were the same for every agent. To complete the first stage, three sounds including the silence sound were permitted. Because of asynchrony and the ratio of sleep time to processing time there was very little possibility of competition for processor time i.e., agents were truly independent, asynchronous, and autonomous.

Each agent was to follow a simple algorithm that would decide how it would call: An agent would average its neighborhood volume average together with the global volume average, and then compare this result to a volume "window" containing the ideal volume. Simple thresholding against this window dictated the decision about whether to be silent, midrange, or loud. The duration of the call was chosen so that the overall distribution of agent selected durations was approximately Gaussian with mean equal to the average of the minimum and maximum values and variance "small."

This first stage was visualized by mapping emitted sounds to colors on a CRT monitor. Tri-level recordings of the color with real time updates exhibited the group’s calling rhythms. The first model was judged successful because it did not appear that the volume emissions were random, and it did seem that agents were reacting to each other’s sounds. However some simulation runs failed. Further investigation provided the first lesson we learned: In rare, random formations some agents did not have enough neighbors to interact with, and as a result, *repetitive* patterns would emerge. This suggested to us that individuals with the capability of forming local neighborhoods only on the basis of fixed *distance* were insufficient for simulating group communication. This called for “smarter” agents.⁷ Henceforth agents were allowed to form their local neighborhoods by maintaining contact with a fixed *number* (usually four) of their nearest neighbors.

Much to our delight, the randomization routine for volume initialization did not affect the simulation. Any transient behavior could die out and cacophony could take over. As the number of agents increased, a phase transition occurred. The simulation reached a stasis i.e., became “steady-state” in the sense that all agents kept repeating the same call. What was believed to have happened was that when an agent had “too many” neighbors after a few calling rounds there was no reason for any of the agents to re-adjust volume levels. From this point on, the maximum size group that was ever tested had seventy-five agents. And henceforth, during initial random placement, the radius of circular region that the group would occupy was adjusted so that “density” of agents would be invariant as group size increased. This increased the reliability of the experiments.

The second stage was to introduce the predator. The predator was introduced in such a way that only the outermost agent nearest the radial line from the center of the group to the predator could sense the predator and sound an alarm. Since the predator moved *away* from the group, it was as if the predator was immediately withdrawn. The agents were made smarter by placing the agents in *states* — normal (cacophonous) state, alert state, or silent state — with a different decision *algorithm* used for each state. The agents were now allowed to make five distinct sounds, three to preserve the cacophonous state, whence the loudest sound would be *rarely* needed and could be used for issuing warnings. This also helped fine tune the ability to maintain the desired background volume level. From an agent’s point

⁷In nature, must agents use a more sophisticated strategy to establish a “local” communicating group within the global group?

of view, the problem at this juncture is to employ successful strategies for situations that are *not* mutually exclusive:

1. Sensing a predator and issuing a warning.
2. Sensing a predator by heeding a warning.
3. Sensing a predator by detecting excessive silence.

The pivotal design decision that must be made before these problems can be considered as an ensemble is whether or not an agent can sense (hear) *while it is calling*. Recall that the simulation requires agents to sleep for the entire duration period they have chosen for their emittance level, *including silence*. Put simply, the question is: Can an agent talk and listen simultaneously? We decided agents could not do so. Agents would therefore have to be more conscious about selecting calling durations so that they could exert greater control over the next scheduled time when they could listen.

With this in mind, if an agent hears a loudest signal, how should it react? Presumably an intruder warning would be as short and as loud as possible. Therefore, if the agent knew the duration of a loudest signal then the agent would have adequate knowledge on which to base its decision about the presence of intruders. But this might lead to the development of hyperactive agents, agents who make *all* sounds as short as possible so they can spend all of their time breathlessly waiting for warning calls. This takes us full circle. For in such a mode of behavior all loudest sounds are as short as possible, and the protocol is defeated. It won't work. Thus we are led to adopt a temporal solution: Issue a warning call by calling as loud as possible for the shortest permitted time, be silent for the shortest allowed time, and call again at the loudest volume for the shortest allowed time. The warning call is terminated by entering the silent state. Now, any loudest volume detected by an agent, will cause it to *switch* to a *hyper-sensing* mode, looking for a silence followed by a loudness which will match the tail end of the warning sequence described. This reasoning motivates agent *planning* and agent *memory*.

We are not through. How will agents detect excessive silence? This is crucial because this is the way most agents will learn about a predator. The first plausible strategy to try is simple thresholding. Would two-thirds of one's neighbors being silent be enough "evidence" of a predator to suggest silence was in order? On the other hand, if agents are overly sensitive to silence by their neighbors, then the reassurance group-calling task is sacrificed, and the group will quickly fall completely silent due to any momentary

silence of just a few members. Since survivability depends on this threshold parameter being very reliable and robust, if it exists it should be easy to identify. **No threshold value that balanced these two factors was obtained through experimentation.**

Another pivotal design decision was called for. A dominance hierarchy within the group is justifiable and would certainly be of use, but that takes us too far afield. Even though in all probability evolution *did* have to simultaneously evolve dominance, mobility, and signaling we shall just have to set it aside. It would be nice to evolve simultaneous solutions to these obstacles — the Alife methodology — but the context has quickly grown too complex, and we were unable to devise any promising lines to pursue towards such ends. We decided to make additional use of agent’s limited memory by having agent’s monitor not only the behavior of loudest callers, but of silent callers as well. Initiating agent silence based on three consecutive silences by any neighbor was the “cheapest” solution. This was added to a “deafening silence” threshold of two-thirds, and did achieve the desired result. However, testing revealed that shortcomings arising from all of our assumptions were starting to mount up. Reliable quieting of all the agents in response to a predator was slower than desired.⁸

One might speculate that evolving numerical constants for the various threshold parameters would improve the group response. We doubt it. There is, in fact, a more serious problem to address. How do agents return to the cacophonous state (i.e., wake up) when the predator has moved on? This called for an all-clear signal. Who should issue the all-clear signal? We conjecture that any number of agents could become “eligible” to issue such a signal, but to observe how the variety of agent strategies fit together, we designated one agent, chosen at random, to be the temporary dominant agent who could test the waters so to speak for the group as a whole.

In the third and final stage of the project, the strategy we implemented for an all-clear signal was to place agents into a cautious state following several minimum time durations of group silence. In this state, the dominant agent can *initiate* a soft call while other agents can respond to *any call* using soft calls. A warning call or a sensed predator will trigger a state change, causing agents to revert to silence, but if agents can remain in the cautious state for three calling cycles, they can revert to the normal ca-

⁸Observe that we are already starting to use up signaling *sequences* and place demands on the amount of “processing” that an agent must perform. What additional processing burden would be imposed by considering, say, a scolding Tsk-Tsk signal consisting of the *lowest* audible call sounded twice in the shortest possible time duration?

cophonous state. Much to our chagrin this worked *better* than the silencing algorithm(s). Cacophony swiftly bloomed over the group of agents. The only times it failed were when one or more agent local neighborhoods were isolated, resulting in a loss of group connectivity. We do not know if this connectivity problem arises in nature for the case of *vocal* contact, but observation suggests it does for the case of *visual* contact. Small groups of birds often break off in flight, or take-off from rest, without the others following.

In reviewing the work of Crawford, we observe that stochastic effects were obtained for free. The thread manager, in trying to service thread requests, introduced the necessary random effects forcing agents to miss calls, wake up too late, et cetera.

Of the future work Crawford considered, we think the most interesting suggestion was to consider the range of the call. A shrill warning will be heard by agents who are not in the local neighborhood, but a wake-up call might be heard by almost all agents. A related issue is directional listening. At present agents don't take into account where sounds emanate from (e.g., from the center or the periphery) only who makes the call. Thinking about such issues could improve the reaction time of the simulation and make it more realistic.

9 What Additional Design Features Are Needed?

In our concluding section, we offer some further analysis of our simulation and investigate a wide variety of additional design features that could, or should, be added to it. In the process, we shall raise several additional unanswered questions regarding the nature of large group communication in simulation.

The first issue we will discuss is that of using simulated evolution to *evolve* group communication strategies. Evidently, one would like to run the genetic algorithm, or the genetic algorithm in conjunction with simulated annealing, to achieve evolutionary results. This brings up a difficult question. On the space of agent strategies, what "fitness" criterion should we impose? Perhaps energy expended in calling, weighted by the time it takes to complete the group task is plausible. It sounds risky. A lot of work could go for naught if evolution failed to achieve any interesting results.

If we were to continue working with a *stationary group*, the most promising avenues to pursue using evolutionary techniques would probably be: (1) searching for good strategies for *shifting* agent's local neighborhoods, either

by changing the number of agents to include in the local neighborhood, or by changing the direction where the neighboring agents in the local neighborhood should be concentrated,⁹ or, (2) searching for optimal parameters to use for the delays and thresholds of the all-clear, wake-up signal.

A tantalizing challenge is to introduce a sensible way of managing dominance. We believe it should be possible to design a *computation* for agents to perform, based on memory and sensory input, that establishes an agent's belief about its relative dominance. As is the case with many desirable features though, this may prove to be a difficult assignment in practice. Note that the existence of such a computational mechanism solves the problem of how agents might be promoted to being dominant, thereby becoming temporarily eligible to issue all-clear signals. Before continuing, we wish to make one aside concerning dominance: If each agent maintains a priority queue for the most silent and most vocal agents in its local neighborhood, can these local queues be merged into a global dominance scheme constituting a "pecking order"?

It is a fact that our stationary group of agents can have multi-valued beliefs about the existence of predators.¹⁰ Hence it would be worthwhile to perform a comparison between the design underlying our simulation and possible non-biological alternatives supporting multi-valued or fuzzy decisioning, including multi-modal decision networks, (continuous) cellular automata, and artificial neural networks.

We have limited our group size to roughly seventy-five agents. We are aware that currently in animation, control of group sizes of up to sixty *thousand* is highly sought after. It has been pointed out to us [2] that there is a working definition by experts of what qualifies as a large group. If K is the (average) neighborhood size and N is the number of agents, then a large group satisfies $N \gg C \cdot 10^K$ for some integer constant C . Under this definition our typical simulation run, which uses $K = 4$ and $N = 40$, is not sufficient. It has also been suggested to us that it would be desirable to provide information about the nature of any phase transitions that arise in the simulation as N increases.¹¹ We believe it is possible to make progress towards discovering what behavioral changes occur with increasing group

⁹What we are really saying is that we want to consider adopting an *elliptical* local neighborhood and then study how it should be oriented on a per agent basis.

¹⁰Presumably agents would also have multi-valued beliefs about dominance, food availability, or the group's security as well.

¹¹Recall that the only phase transition observed in the Crawford simulation was the stasis that was reported for $N > 75$.

size, but only with significantly more powerful computers at our disposal.

As the design for our simulation developed, it became necessary to change our emphasis from agents issuing sounds, to agents issuing sequences of sounds representing calls. We did not investigate to any significant extent what the consequences would be of imposing “rest periods” after sequenced calls were made, nor did we follow-up on the question about whether or not agents should be able to accept and act upon sensory input in mid-call i.e., break off a call. It would be interesting to know if changing such assumptions would change any of our results.

Kauffman speculates on the nature of coordination (his version of the synchronization problem) based on experiments involving lattices of agents communicating with nearest neighbors. His motivation is to understand how decentralization of groups into units, or departments, affects group goals. The findings summarized in his book [25, pages 269–270] included that said agents should ignore some small percentage of the signalers *in their neighborhoods*.¹² This leads one to ask a related, albeit slightly different, question: How *often* must receivers listen for signals?

In addition to synchronization, another rationale for group communication is cooperation. An important example is cooperation for exploiting a resource such as food. There is some related work done in the fields of robotics and computational ecosystems¹³ that we would like to consider. Glance and Hogg [13] are motivated by the problem of an agent cooperating for the social good of the group versus defecting for the good of itself. They appeal to Braess’ Paradox which demonstrates the existence of social dilemmas in a computational domain. The example they refer to shows that when agents individually act for their own good, *additional* resources can lower overall group performance. The discussion in [13] has implications for the simulation described in the previous section. The agent group does not really need *all* individuals to devote their efforts to the highest priority task — sounding a warning — so it should be optimal for agents to learn strategies for allocating tasks such as sounding alerts or testing for an all-clear. But now we have raised the possibility that this might lower the effectiveness for doing so. In any event, this suggests agents must possess the capability of

¹²To be precise, in the experiments he describes, each signaler within the receiver’s neighborhood had a probability of .95 of being listened to.

¹³In [21], a computational ecosystem is defined as large collection of locally-controlled, asynchronous and concurrent processes interacting in an unpredictable environment. This applies not only to biological communities but web based autonomous agents (softbots and knowbots) and distributed intelligence architectures.

learning to *manage* a set of behavioral rules. Such high-level cognitive capabilities detract from the goal of formulating the simplest design necessary to support group communication.

Cooperation, and the emergence of cooperation, have been studied in the Alife community using the well-known game of the Prisoner’s Dilemma. We reference the study which we think best illustrates how this might be relevant for group communication. Ito and Yano [23] designed experiments to demonstrate the emergence of cooperation in a mobile society of agents who were forced to play the Prisoner’s Dilemma. For our purposes, the game is a canonical example of two agents engaging in a *one-on-one* interaction. The success Ito and Yano achieved in simulating cooperation was brought about by agents exchanging both their playing histories (information disclosure) and their inherited strategies (survivability of the strategies). With the intent of improving our simulation, the design problem requires that we decide what “exchange” means. We are on shaky ground. Is exchange to be accomplished used *cues*¹⁴ or signals? If it is by signals, then does this mean that we will need multiple sensory channels?

A second study shows that the exchange problem is persistent. Selection of strategies *without* memory, for the purpose of evolving social laws (see below), was investigated by Walker and Wooldbridge [47] through a series of experiments designed to study how to reduce aggression in groups. They obtained promising results when agents were able to *communicate* their strategies to neighbors. We know of no biologically inspired communication simulation that has incorporated disclosure elements into its design.

It would be beneficial to be able to *observe* the evolution of agent strategies in the biological world. It might offer clues as to how signaling about strategies could take place. Perhaps this is not possible because it is equivalent to observing evolution on a grand scale itself. As evidence, we cite Youssefmir and Huberman [50] who observe, in their simulation, evolution of agent strategies that closely reminds us of several Alife evolution simulations pertaining to *species*. For example, they describe punctuated equilibrium occurring among the mixes of agent strategies and they characterize the transitions that occur between strategies agents evolve as equilibriums encountered during explorations of strategy space using random search.

We would like to see additional auditory cues propagated within our

¹⁴By a cue we mean information that is *always* available to a receiver. For example, in nature many organisms do not signal that they are poisonous, instead their coloring is used as a cue that they are poisonous.

agent group, and we would like to know how private one-on-one interactions fit into our scheme of agents making calls to, and on behalf of, the entire group. We can once more draw from an example that will be familiar to all. When eating lunch in a crowded and noisy open-air patio, flocks of sparrows usually appear seeking crumbs. The arena is chaotic for both people and birds. One can observe the birds forming local neighborhoods, and one can observe group communication when food resources are found — a mad rush, flight, etc. We assume this is another instance of what Elgar [11] claims for sparrows: they establish foraging flocks by giving chirrup calls if the resources are divisible, and the time for others to join in is inversely proportional to the rate of call. This is also consistent with what Caine et al [6] have to say about tamarinds: “To the extent that a species is dependent on intra-group cohesion for critical daily activities and protection, food calls may benefit the caller by drawing its allies near, even if calling increases feeding competition.” The more difficult question to ask is: Are calls such as mating calls and dominance calls private, propagated, or (assuming a local neighborhood exists) only available to the local neighborhood? Our dilemma is how to integrate signaling into the simulation so that it can seamlessly support these possibilities. In passing, we mention that another candidate signal that fits nicely within this framework is the territory *defense* signal, because it can take on both a group and individual character.

There is another slippery issue to discuss, and we will make only a brief digression in order to consider it before turning to our most pressing need, the need for agent mobility. In nature, communication occurs in the presence of (or does it give rise to?) *social laws*. We are borrowing our understanding of this concept from multi-agent societies consisting of robots. An example is in order. In robotics, a social law can be used to keep robots from colliding. In nature a social law can be used for preservation e.g., males defend while females and juveniles flee. For our simulation is there a social law that would govern the wake-up sequence that must take place when group silence has taken hold following predator detection? Formal models of social laws are considered by Shoham and Tennenholtz [39] who use them to prove, in a technically precise way, that the problem of generating a “useful” social law is NP-complete. This is troubling. In our quest for minimalism in a simulation there is little room for NP-complete features.

For our simulation, agent mobility is the next feature that must be introduced. Motion in *large* groups will be problematic. From *small* group robotics, performed by simulation and using physical robots, lessons have been learned that should be heeded. In a study by Balch and Arkin [3],

a group of four simulated robots was given the task of moving in such a way as to maintain a rigid formation. It was found that signaling and receiving between all pairs was most effective for this task. Their study cautioned, however, that for humans (viz., biological agents) the opposite appears true. One leader/transmitter and three follower/receivers are required to maintain group formation. They point out the obvious: The sensory demands placed upon sensory agents (e.g., visual or aural tracking) would have to be limited to a very few individuals even in small groups. This research argues for additional work to be performed concerning the local organization of neighborhoods. It is of interest to note that Balch and Arkin found that the most successful *geometry* for their groups (i.e., type of formation that could be rigidly maintained) was leader-led columns. Are these the most primitive emergent mobile groups?

We plan address the question of mobility by initiating a theoretic investigation into a variant of swarm automata — interacting mobile automata that can communicate only with nearby automata by setting local “interrupt” timers. We should hasten to point out that our study will address only the two-dimensional group mobility problem. We have no thoughts on how to organize a group in three dimensions nor how to model predators in such an environment. One simple question we are unable to answer is: What path through the group would a predator follow if the group silences before it can detect any member? There is much that remains to be done before satisfactory solutions to the problem of designing our top priority feature, agent mobility, will be satisfactorily completed.

References

- [1] D. Ackley, M. Littman, Interactions between learning and evolution, *Artificial Life II*, (ed. C. Langton et al), 1992, 487–509.
- [2] A. Adamatsky and C. Melhuish, *Private communication*, October 21, 1987.
- [3] T. Balch and R. Arkin, Motor schema-based formation control for multiagent robot teams, *Proceedings of the First International Conference on Multiagent Systems*, (ed. V. Lesser and L. Gasser), MIT Press, Cambridge, MA, 1995, 10–16.
- [4] J. Bates, The role of emotion in believable agents, *Communications of the ACM*, **37** (July 1994), 122–125.

- [5] R. Beckers, O. Holland, and J. Deneubourg, From local interactions to global tasks: stigmergy and collective robotics, *Artificial Life IV*, (ed. R. Brooks and P. Maes), 1994, 181–189.
- [6] N. Caine, R. Addington, and T. Windfelder, Factors affecting the rates of food calls given by red-bellied tamarinds, *Animal Behavior*, **50** (1995), 53–60.
- [7] B. Cole, Fractal time in animal behavior; the movement of *drosophila*, *Animal Behavior*, **50** (1995), 1317–1324.
- [8] J. Crawford, Temporal flocking and cacophony — simulating agent communication in a noisy environment, *Honors Thesis in Computer Science*, University of Richmond, 1997.
- [9] P. de Bourcier and M. Wheeler, The truth is out there: the evolution of reliability in aggressive communication systems, *Fourth European Conference on Artificial Life*, (ed. P. Husbands and I. Harvey), MIT Press, Cambridge, MA, 1997, 444–453.
- [10] M. Dyer, Toward synthesizing artificial neural networks that exhibit cooperative intelligent behavior: some open issues in artificial life, *J. of Artificial Life*, **1** (1994), 111–134.
- [11] T. Elgar, House sparrows establish foraging flocks by giving chirrup calls if the resources are divisible, *Animal Behavior*, **34** (1986), 169–174.
- [12] H. Gerhardt and G. Klump, Masking of acoustic signals by the chorus background noise in the green tree frog: a limitation on mate choice, *Animal Behavior*, **36** (1988), 1247–1249.
- [13] N. Glance and T. Hogg, Dilemmas in computational societies, *Proceedings of the First International Conference on Multiagent Systems*, (ed. V. Lesser and L. Gasser), MIT Press, Cambridge, MA, 1995, 117–124.
- [14] D. Golberg, *Genetic algorithms in search, optimization, and machine learning*, Addison-Wesley, Reading, MA, 1989.
- [15] M. Hausberger, M.-A. Richard-Yris, L. Henry, L. Lepage, and I. Schmidt, Song sharing reflects the social organization in a captive group of European starlings (*Sturnus vulgaris*), *J. of Comparative Psychology*, **109** (1995), 222–241.

- [16] M. Hauser, *The Evolution of Communication*, MIT Press, Cambridge, MA, 1996.
- [17] T. Haynes and S. Sen, Evolving behavioral strategies in predator and prey, *Adaptation and Learning in Multi-Agent Systems, IJCAI '95 Workshop Proceedings, Lecture Notes in Artificial*, **1042** (1996), (ed. G. Weiss and S. Sen), Springer-Verlag, 113–126.
- [18] J. Hodgins and D. Brogan, Robot herds: group behaviors for systems with significant dynamics, *Artificial Life IV*, (ed. R. Brooks and P. Maes), MIT Press, Cambridge, MA, 1994, 319–324.
- [19] P. Hogeweg, MIRROR beyond MIRROR, puddles of LIFE, *Artificial Life*, (ed. C. Langton), Addison-Wesley, Redwood City, CA, 1989, 297–316.
- [20] O. Holland, C. Melhuish, and S. Hoddell, Chorusing and controlled clustering for minimal mobile agents, *Fourth European Conference on Artificial Life*, (ed. P. Husbands and I. Harvey), MIT Press, Cambridge, MA, 1997, 539–548.
- [21] B. Huberman and S. Clearwater, A multi-agent system for controlling building environments, *Proceedings of the First International Conference on Multiagent Systems*, (ed. V. Lesser and L. Gasser), MIT Press, Cambridge, MA, 1995, 171–176.
- [22] J. Hutchinson, J. McNamara, and I. Cuthill, Song, sexual selection, starvation and strategic handicaps, *Animal Behavior*, **45** (1993), 1153–1177.
- [23] A. Ito and H. Yano, The emergence of cooperation in a society of autonomous agents — the Prisoner’s Dilemma game under the disclosure of contract histories, *Proceedings of the First International Conference on Multiagent Systems*, (ed. V. Lesser and L. Gasser), MIT Press, Cambridge, MA, 1995, 201–208.
- [24] M.-T. Kaltwasser, Acoustic signaling in the black rat (*Rattus rattus*), *J. of Comparative Psychology*, **104** (1990), 227–232.
- [25] S. Kauffman, *At Home in the Universe*, Oxford University Press, 1995.
- [26] J. Koza, *Genetic Programming, On the Programming of Computers by Means of Natural Selection*, MIT Press, Cambridge, MA, 1992.

- [27] P. van Laarhoven and E. Aarts, *Simulated annealing : theory and applications*, Kluwer, Boston, MA, 1988.
- [28] M. Lewis, On the asymptotic speed of a stochastic invasion, *Abstracts of the AMS*, **19** (1998), 392.
- [29] S. MacDougall-Shackleton and S. Hulse, Concurrent relative and absolute pitch processing by european starlings (*Sturnus vulgaris*), *J. of Comparative Psychology*, **110** (1996), 139–146.
- [30] B. MacLennan, Synthetic ethology: an approach to the study of communication, *Artificial Life II*, (ed. C. Langton et al), Addison-Wesley, Reading, MA, 1992, 631–658.
- [31] P. Maes, Artificial life meets entertainment: lifelike autonomous agents, *Communications of the ACM*, **38** (November 1995), 108–114.
- [32] P. McGregor and T. Dabelsteen, Communication networks, in *Ecology and Evolution of Acoustic Communication in Birds*, (ed. Kroodsma and Miller), Cornell Univ. Press, Ithaca, NY, 1996.
- [33] P. Palanque, R. Bastide, Temporal aspects of usability: time modeling in Petri Nets for the design of interactive systems, *SIGCHI Bulletin*, Volume **28**, Number 2, 1996, 43–46.
- [34] D. Powell (ed), Group Communication, *Communications of the ACM*, **39** (April 1996), 50–70.
- [35] H. Paterson, The recognition concept of species, *S. African Journal of Science*, **80** (1984), 312–318.
- [36] T. Ray, An approach to the synthesis of life, *Artificial Life II*, (ed. C. Langton et al), Addison-Wesley, Reading, MA, 1991, 371–408.
- [37] T. Ray, Evolution of differential multi-threaded digital organisms, *Artificial Life VI*, (ed. C. Adami et al), MIT Press, Cambridge, MA, 1996, 295–304.
- [38] C. W. Reynolds, Flocks, herds, and schools: a distributed behavioral model (Proceedings of SIGGRAPH '87), *Computer Graphics* **21**(4), 1987, 25–34.
- [39] Y. Shoham and M. Tennenholtz, On social laws for artificial agent societies: off-line design, *Artificial Intelligence*, **73** (1995), 231–252.

- [40] K. Sims, Evolving 3D morphology and behavior by competition, *Artificial Life IV*, (ed. R. Brooks and P. Maes), MIT Press, Cambridge, MA, 1994, 40–48.
- [41] C. Sommerer and L. Mignonneau, “A-Volve” an evolutionary artificial life environment, *Artificial Life V*, (ed. C. Langton and K. Shimohara), MIT Press, Cambridge, MA, 1997, 167–175.
- [42] C. Stacier, D. Spector, and A. Horn, The dawn chorus and other diel patterns in acoustic signaling, in *Ecology and Evolution of Acoustic Communication in Birds*, 1996, 426–453.
- [43] A. Stevens, Pattern formation induced by attractive diffusing and non-diffusing media, *Bulletin of the AMS*, **19** (1998), 391.
- [44] D. Terzopolous, X. Tu, and R. Grzeszczuk, Artificial fishes with autonomous locomotion, perception, behavior, and learning in a simulated physical world, *Artificial Life IV*, (ed. R. Brooks and P. Maes), 1994, 17–27.
- [45] P. Todd and H. Yanco, Environmental effects on minimal behaviors in the minimat world, *Adaptive Behavior*, **4** (1996).
- [46] M. Tuttle, L. Taft, and M. Ryan, Evasive behavior of a frog in response to bat predation, *Animal Behavior*, **30** (1992), 393–397.
- [47] A. Walker and M. Wooldbridge, Understanding the emergence of conventions in multi-agent systems, *Proceedings of the First International Conference on Multiagent Systems*, (ed. V. Lesser and L. Gasser), MIT Press, Cambridge, MA, 1995, 384–389.
- [48] G. Werner and M. Dyer, Evolution of communication in artificial organisms, *Artificial Life II*, (ed. C. Langton et al), 1992, 659–688.
- [49] G. Werner and P. Todd, Too many love songs: sexual selection and the evolution of communication, Fourth European Conference on Artificial Life, (ed. P. Husbands and I. Harvey), MIT Press, Cambridge, MA, 434–443.
- [50] M. Youssefmir and B. Huberman, Resource contention in multiagent systems, *Proceedings of the First International Conference on Multiagent Systems*, (ed. V. Lesser and L. Gasser), MIT Press, Cambridge, MA, 1995, 398–403.