A Simple Model for the Evolution of Communication

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Abstract

This paper investigates the evolution of communication among autonomous robots in the real world. A simple model has been constructed as a first step, in which a population of artificial organisms inhabits a lattice plane. Each organism communicates information with neighbors by uttering words. A common language typically evolves. We have analyzed evolutionary dynamics in this system, and have begun to implement it with a population of small mobile robots.

1.0 Introduction

This paper reports on the current state of our efforts to generate and evolve primitive "languages" in robots, allowing them to perform various tasks more effectively, by sharing information during social exchange. Section 2 describes the construction of an inner image and the generation of a primitive language between two artificial organisms, termed LangEs, which are controlled by "associatrons," a model of associative memory with a neural network structure. Section 3 describes a model of language generation by evolution and learning among a population of LangEs. Based on this model, the results of preliminary experiments are described in Section 4. In Section 5, we discuss how we are attempting to apply and extend the model to a real-world robots system, and describe the current system. Section 6 summarizes the paper.

2.0 Language Learning between Two LangEs

2.1 World Image Construction

The human brain is able to self-organize in such a way that it can hold relations among phenomena in the outer world. When observing an object, the brain gives rise to a pattern of excitation, corresponding to the attributes of that object. One of the significant functions of the brain is to synthesize and memorize pertinent stimulus patterns while at the same time maintaining the appropriate relations among them. The relations stored in the brain's memory make up a kind of inner model of the outer world. We call this inner model a "world image." For example, when a human sees and eats an apple, information sensed by a variety of receptors -- the eyes, ears, and mouth -- is transformed to corresponding stimulus patterns in the brain (Fig. 1). Upon hearing the word "apple," this sound is also transformed to a stimulus pattern in the brain. Then the attributes of apples and the word "apple" are associated and mutually recalled. From a simple input, the word "apple," a whole host of other attributes of apples can be recalled. This model is consistent with recent studies of functional brain imaging in humans [1]. Whether or not correct in all its details, something similar to this must underly memory.

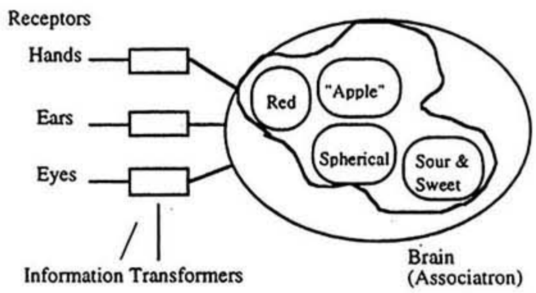

Fig. 1 Transformation of information.

We have constructed artificial organisms (LangEs) that are able to construct such a kind of inner model of the outer world in much the same way. The brains of LangEs are realized by "associatrons," a model of associative memory based on simple neural networks proposed by Nakano [2]. These are similar to networks later analyzed by Kohonen with "correlation matrices" [3]. Items to be memorized are represented as n-dimensional vectors, whose elements take the values -1, 0, or 1.

$$\mathbf{x}^{(p)} = (x_1^{(p)}, x_2^{(p)}, \dots , x_i^{(p)}, \dots, x_n^{(p)})^t,$$

where p is the index of the items, and t denotes transposition. Items are memorized as the sum of the auto-correlation matrices of the vectors, that is,

$$M = \sum_{p=1}^{k} \mathbf{x}^{(p)} \cdot \mathbf{x}^{(p)\,t}.$$

Memorized vectors are recalled by

$$\mathbf{z} = sgn(sgn(M) \cdot \mathbf{x})$$

where $sgn(u)$ is a threshold function, defined as

$$sgn(u) = \begin{cases} -1 & \text{if } u < 0, \\ 0 & \text{if } u = 0, \\ 1 & \text{if } u > 0. \end{cases}$$

In the event that this function is applied to matrices or vectors, the above operation is carried out for each element of matrix or vector. If most elements of input vector $\mathbf{x}'$ are equal to the corresponding elements of $\mathbf{x}$, and the rest are 0s, then the recalled vector $\mathbf{z}$ will be similar or equal to $\mathbf{x}$. This means that the associatron can recall the entire memorized pattern from only part of it.

This function can be implemented with a mutually-connected neural network [2][3]. Using the nomenclature of Nakano [2], an associatron is composed of "neurons" which correspond to the elements of an item vector. Individual neurons are connected to one another in pairs. When an input pattern is fed in and the resulting excitation pattern arises in this neural network, the synaptic weights are increased by the products of input values of neurons on both sides of the synapse. At the same time, individual neurons stimulate other neurons through synaptic connections. The stimulation strength is the product of the output from the neuron and the quantized value of synaptic weight (1, 0, or -1, according to the value, plus, zero, or minus, respectively). Each neuron takes a 1, 0, or -1 value by majority decision; that is, it takes 1 if there are more stimuli 1s than -1s, and it takes -1 if there are more -1s than 1s.

2.2 Environment for Language Generation

Suppose that LangEs have been fully trained on the items to be discriminated. Then suppose the LangE senses an object, so that an excitation arises in the LangE's brain, corresponding to the attributes of that object. For example, when a LangE meets a lion, the composition of stimulus patterns which correspond to the attributes of the lion -- "brown," "with hair," and "big" -- may arise in its brain. When the LangE encounters a rabbit, the composition of stimulus patterns of its attributes -- "white," "with hair," and "with long ears" -- arises in the same way. Suppose further, that the same part of the stimulus pattern is active for the same attribute. For example, upon sighting a lion or rabbit, the attribute "with hair" excites the same state in the same position of the stimulus pattern. By taking the intersections of the stimulus patterns, it is possible to extract the attribute "with hair." This operation is available through the random stimulation of attributes to the associatron. Objects and attributes extracted by random stimulation are treated in the same manner and memorized as concepts. At the same time, names are given to them.

It might appear that attributes are all defined *a priori*, so that LangEs give only one-to-one correspondences between the exciting patterns and names. This is not, however, the case. Consider the following example: A lion has attributes "brown," "with hair" and "dangerous," and a bear has attributes "black," "with hair," and "dangerous." Then, the common attributes for the two objects are "dangerous and with hair." This is regarded as one concept, because if no other objects were to exist in the world, both of the attributes would never be discriminated between.

When two LangEs recognize an object, they recall the concepts in relation to the object expressed by the stimulus patterns in their world images. They then recall words from the concepts and speak them to each other. Only words corresponding to concepts are treated in this study, in order to initially avoid the complication of syntax. At the beginning of the experiment, words corresponding to objects are determined randomly and independently, so two LangEs would generally have different words for the same objects. Because they shared a common experience, each LangE feeds the association of the words which the other LangE says and the concepts which it recalls for itself, into the associatron. Through repetition, the words of two LangEs corresponding to the same objects or the same attributes will gradually become similar, and finally become identical. Then when one LangE hears the words the other LangE utters, it can recall the same concepts in its brain that the other recalls. At this stage, they share their world images through the medium of words. It can be said that a primitive language has been generated by the two LangEs, in some ways similar to pidgin.

3.0 Language Evolution among a Population of LangEs

3.1 Environment and Conversation

Let us enlarge the scope of the model above, and explore how language might evolve in an artificial world in which many LangEs reside and repeatedly produce offspring [4]. Suppose that LangEs are placed in a two-dimensional toroidal grid, and cannot move out of their location. Each LangE is able to construct its own world image through its associatron. Stimulus patterns which have been fed into the associatron consist of both the patterns for a set of objects and the names given to those objects and/or concepts. Each LangE L_{ij} (i and j denote the location in the grid plane) has, as its internal values indicating its state, the scores P_{ij}, the age A_{ij}, an inborn value GA_{ij} related to the selection pressure, and the cross-correlation matrix M_{ij} which is the phenotype of, and initially equals, the inborn matrix GM_{ij}.

Suppose a LangE in some location and its surrounding eight neighbors have a common experience by observing an object, recalling the words for it, speaking them to each other, and feeding into the associatron memory the association of the words spoken by other LangEs and the patterns for the object. Assume that only one-to-one conversations are held between the LangE in the location of the object and its eight immediate neighbors. When the words spoken by another LangE matche the words the focal LangE speaks, both are rewarded with some value g, which is added to their scores, P_{ij}. When the words spoken by a pair of LangEs are not the same, then g is subtracted from the scores of both. When a conversation has been established in this way, then an object may be observed by only one LangE, which transmits information through words alone, prompting the other LangE to recall the full stimulus pattern corresponding of the object which it has not, itself, observed.

3.2 Alternation of Generations

The ability to communicate through language can be evolved. One way to accomplish this is as follows: First, an initial random population is created in the environment. A location to be the center of conversations and an object to be observed, by the nine around it, are randomly selected. The LangEs in a neighborhood then hold eight one-to-one conversations; these will cause learning by the neural networks. Then another location and another object are selected, and the conversations are held again. And so on. Every lattice point is selected to be the center of conversation one time. Next, a LangE is removed, according to a probability, and an offspring is created at the location of the removed LangE. The probability of the LangE at ij to die is $Select(A_{ij}, P_{ij}, GA_{ij})$,

$$Select(A_{ij}, P_{ij}, GA_{ij}) = 1 / \{ 1 + exp (-s*((A_{ij} - c*P_{ij}) / GA_{ij} - 1)) \},$$

where c and s are chosen to be positive constants. This is calculated on each LangE independently at every turn-around. When a LangE dies and is removed from the grid, then an offspring is produced at that location, thus keeping the overall population size stable. The parents for the replacement are found by first selecting a pair of LangEs from the eight neighbors, in proportion to the following weights:

$$Parent(P_{ij}) = \Phi(P_{ij})^2 \ / \ \sum_{|i-k| <= 1,\ |j-l| <= 1} \Phi(P_{kl})^2,$$

where $\Phi(x)$ equals x (if $x>0$) or 0 (if $x<=0$). Mated genome strings cross over at randomly-selected crossing sites. Inheritance is Mendelian, rather than Lamarckian; which is to say that the information passed to the next generation comes not from the learned matrices M_{ij}, but from the inborn matrices GM_{ij}. Mated genome strings cross over, and mutation is performed on a bit-by-bit basis, with some probability. The age A_{ij} and the score P_{ij} of the offspring are set to be zero when the new LangE is created.

These processes -- conversations, selection, replacement -- are repeated again and again. We will refer to the passage of time for one repetition as one year.

4.0 Preliminary Experiment

4.1 Conditions and Measurements

We have conducted some preliminary experiments similar to those described in the previous section. The size of the environment was 5 x 5, containing 25 LangEs. The length of the input/output field of each associatron was 55 bits, of which 50 bits were for the object patterns, and 5 bits were for the corresponding words. There were six objects to be recognized; the reward or penalty, g, was 1; and the mutation probability, e, was 1/10. In $Select()$, c = 1 and s = 5. GA_{ij} and the elements of GM_{ij} for the initial population were assigned randomly from the interval $100<=GA_{ij}<=300$, and $-5<=GM_{ij}(x,y)<=5$, respectively. Six measurements were defined for analyzing the results of experiments. The average for each measurement was calculated for all LangEs for every 100 years. *Life expectancy* is the average age of a LangE when it dies. *Selection pressure* ($=GA_{ij}$) is the inherited parameter used in *Selection()*. The higher the *selection pressure*, the less likely the LangE is to die. *Learn length* is the average age of a LangE when each name given by that LangE and the names given by more than three neighbors become coincident, that is, the average age when the LangE shares a vocabulary with more than three neighbors. *Genome level* is the average number of surrounding LangEs which have the same vocabulary as that of the newborn LangE. *Language coincidence* is the average rewarded score per year -- the maximum is 16, when 8 as a center and 8 times 1 as a neighbor, and the minimum is -16. Language unity means that all of the LangEs share an identical vocabulary; that is, each object is given its own unique name by all of the LangEs in the population. *Language transition* is the number of times one language unity is destroyed and replaced by another. When the *language transition* converges to some value other than zero, then the language will change continuously.

4.2 Evolutionary Dynamics

The results are shown in Fig. 2 and Fig. 3. *Language coincidence* shows a tendency to increase; in other words, the scores acquired by LangEs increase through evolution, as expected. *Life expectancy* and *selection pressure* also increase during an initial stage, and then show a tendency to converge. *Genome level* is negatively correlated with *learn length* because in general, the higher the *genomelevel* the less need there is to learn. Thisis apparent from the figures. It is also found that *genome level* was correlated with *language coincidence*. *Learn length* shows a single peak, and then decreases. The cause of the decrease seems to be that it becomes easier to learn as more of the language is shared.

It is interesting that *language transition* does not converge to zero. This is because of the rapid alternation of generations. Fig. 4 shows one instance where there was a transition of the word used for the name for an object by all 25 LangEs. For this illustration each name is represented by a letter of the alphabet for simplicity, though it was actually a 5-bit binary string in the experiments. First, the word "J" for the objects is shared by all LangEs. Then, another word, "K" arises and spreads, generate two dialects, "J" and "K," over different regions. The accumulation of mutation, propagation delay and the effects of inheritance produce very complex dynamics, while learning by the associatron and selection of parents have large effects on language unification.

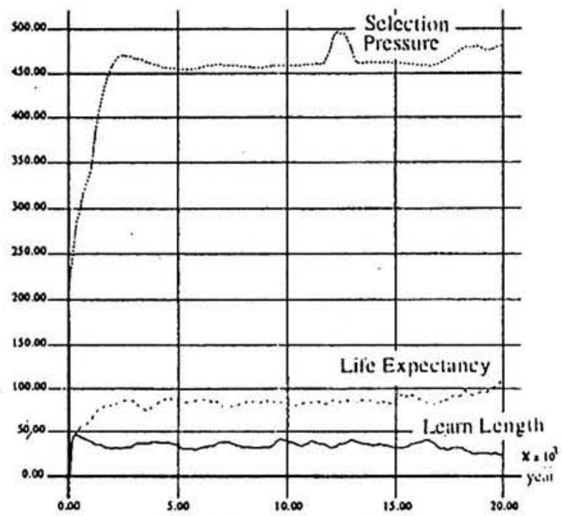

Fig. 2 Simulation results (1)
(Learn Length, Life Expectancy, Selection Pressure).

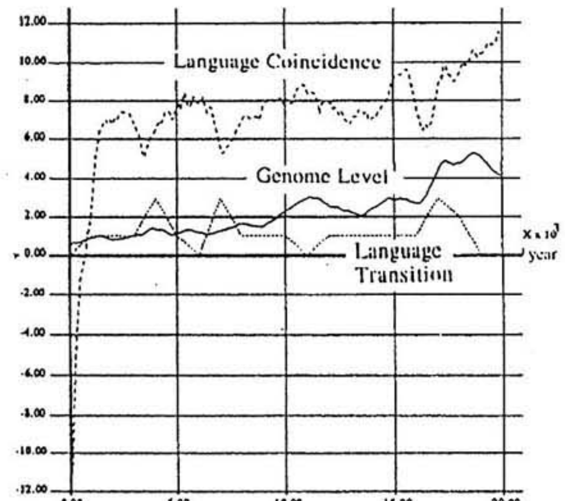

Fig. 3 Simulation results (2)
(Language Coincidence, Genome Level, Language Transition).

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 J J J J J   I J J J J   K J K J K   K J K K K
 J J J J J   J J J J J   K J J J O   K J K K J
—J J J J J — J J J J J — J J K J J — K J K J J —
 J J J J J   J K J J J   J p K J J   K K K J J
 J J J J J   K K J J J   K K K J J   K K K J J
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Fig. 4 Examples of name transition

5.0 LangE Model on a Robots System

5.1 Direction

We are now investigating the evolution of communication among the autonomous robots in the real world, based on the foregoing model for the evolution of communication. Is it possible for autonomous robots that have self-organizing brains to extract sensation patterns from their various sensor inputs, and then to give them commonly understood meanings that permit them to communicate effectively? Is it possible for them to allocate various tasks dynamically, and then to cooperate among themselves? It will be necessary to address several issues:

1) Motivation for communication

If the robots can acquire enough information on other robots by modeling their world internally, then their communication requirements will be correspondingly decreased. Therefore, it is important for the models of evolving communication to consider the motivation for that communication. All of the outputs, including message sending, should be subject to evolution and autonomously defined in our robots, to the extent that even silent robots should be permitted.

2) Simulation and physical realization

It is very difficult and may take as much time for detailed simulations as it would take to build the actual robots. At the same time, it is also impractical to build and observe many actual robots during many generations. Therefore, we plan to adopt a hybrid simulated/embodied selection regime [5]. Large numbers of simulated robots are examined in simulation, but only the promising subset of these are actually built and examined, thereby reducing the scope of the problem.

3) Task allocation and information transfer

It is important for robots be able to switch tasks autonomously, based both on environmental stimuli and on their interactions with other robots. The information which is exchanged among robots is likely to depend on the complexity of tasks in which the robots are engaged. Several encouraging results are described in [6], which suggest that very simple mechanistic interactions between individuals are sufficient to allow the colony to maximize food intake and other quantities related to fitness.

5.2 Current Robots System

At the UCLA Commotion Laboratory, several projects are under way that study issues pertaining future robotic platforms [7]. The system available to us consists of ten R3 robots from IS Robotics Inc. and an 8 meter x 7 meter arena which has been set aside for remote experimentation. The R3 is a small, autonomous mobile robot about 40 cm both in diameter and in height. Each of the robot has been outfitted with a Linux operating system running on 486/DX2 processors. The sensor array of the robot includes infrared proximity sensors, bump sensors, shaft encoders, and power status indicators. The robot moves using a differential drive and can manipulate objects using a force-sensing gripper subsystem. A pair of Proxim radio modems is dedicated as a wireless serial link between each R3 and its basestation. We believe that this system, which is still in early stages of implementation, is well suited to our needs.

6.0 Conclusion

It is important to put the various abstract results from artificial life research into the real world. This paper investigates the evolution of communication among autonomous robots. A simple model has been constructed as a first step, in which a population of artificial organisms inhabits a lattice plane and each repeats communicating information with neighbors by uttering words. The model has been implemented, we have analyzed its evolutionary dynamics, and have begun to implement it with a population of small mobile robots.

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