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Abstract

This paper explores the evolution of communication in a community of agents. Experimental results show that agents are capable of evolving a shared lexicon describing robot behavior. Categorization of perceptions arises as an emergent property of the imitative interaction of agents.

1 introduction

The origin and evolution of language is an excellent domain for studying fundamental questions of artificial life research. Previous work by Arita[1], Steels[2], Hasimoto and Ikegami[3], and Kirby[4], among others, have shown that we are able to explore important issues such as emergence, self-organization and cultural evolution within this framework.

The emergence of symbolic communication is one of the most significant transitions in the evolution of language and at the core of what is desired for adaptive robotics. This implies the ability to acquire concepts, to ground symbols into concepts, and to propagate those symbols in a community of other agents

Previous work on evolving symbolic communication systems was largely based on the approach proposed by Hurford[5]. The core of this model is a pair of lexical matrices in which a fixed collection of symbols and meanings are probabilistically correlated. An underlying one-to-one correspondence between symbols and meanings is assumed. The categorization and generalization capabilities of agents are limited to a few cases of synonymy and homonymy. Most work based on lexical matrices have focused on the evolutionary behavior of communicative strategies [6][7]. We believe that for a symbolic communication system to properly work it must adequately capture patterns of categorization.

McLennan [8] has demostrated that finite state machines (FSMs) can be used to evolve a highly coordinated symbolic communication system. This holds much promise. For example, Lee et al[9] found that FSMs can be used as appropriate models for symbol grounding. Moreover, these models can readily discriminate a potentially infinite collection of inputs.

This paper extendes the study of Lee et al [9] from a single agent to the emergence of symbolic communication in a population of agents. In our model, agents communicate by producing an utterance in response to a sensory stimulation. The communicative behavior of agents is produced by finite state transducers. We assume that communication is an evolutionary behavior: agents who communicate well produce more offspring. Agents achieve lexicon formation by imitation: the communicative success of an agent depends on his imitative ability.

Experimental results show that our model is capable of producing an emergent lexicon describing robot behavior in a population of agents. Furthermore, we show that meaningful categories of robot behaviors emerge in our model without any explicit selective pressure for categorization.

2 The model

The experiments were conducted by using the methodology proposed by Steels[10], inspired by the language game of Wittgenstein[11]. Under this framework, an experiment in artificial language evolution always has the following ingredients: (1) an interaction protocol for the agents, (2) an agent architecture, (3) an environment, and (4) a set of measures for success in communication.

2.1 Interaction protocol

The model considers a population of communicating agents. During the simulation, an agent interacts with a subpopulation of randomly selected agents by

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using a simple pairwise imitation game: the agent attempts to match the utterance produced by other agents in response to a particular sensory stimulation.

2.2 Agent architecture

The communicative behavior of agents is produced by finite state transducers (FSTs) [12]. An extension of the Mealy machine model was formulated for this purpose as follows. A *one-symbol output Mealy machine* is a 6-tuple $(Q, \Sigma, \Gamma, \delta, \phi, q_0)$, where

1. Q is a finite set of states,
2. Σ is the input alphabet,
3. Γ is the output alphabet,
4. $\delta : Q \times \Sigma \to Q$ is the transition function,
5. $\phi : Q \times \Sigma \to \Gamma$ is the output function,
6. $q_0 \in Q$ is the start state.

Let $M = (Q, \Sigma, \Gamma, \delta, \phi, q_0)$ be a one-symbol output Mealy machine and $w = w_1 w_2 \cdots w_n$ be a string over the input alphabet Σ. The machine M produces the output symbol u from the output alphabet Γ in response to input w, $M(w) = u$, if a sequence of states $r_0, r_1, \ldots, r_n$ exists in Q with the following conditions:

1. $r_0 = q_0$
2. $\delta(r_i, w_{i+1}) = r_{i+1}$ for $i = 0, \ldots, n-1$, and
3. $\phi(r_{n-1}, w_n) = u$

The output symbol u in $M(w) = u$ is viewed as the utterance that is produced by the agent described by M to verbalize the situation encoded by the input string w. The lexicon of a population of agents P for a set of perceptions W, $L(P, W)$, is defined as the collection of all different output symbols $u \in \Gamma$ produced by all agents $a \in P$, in response to all inputs $w \in W$.

At each step of the simulation, two agents are selected according to their communicative efficiency. These agents produce a new offspring by means of genetic operators. One-point recombination and point mutation operate on a linear representation of agents. M is represented as linearly by:

$$q_{0,0}u_{0,0}q_{0,1}u_{0,1}\cdots q_{1,0}u_{1,0}q_{1,1}u_{1,1}\cdots q_{|Q|,|\Sigma|}u_{|Q|,|\Sigma|}$$

where $q_{i,j} \in Q$ indicates the table entry at row i and column j of the tabular version of δ, $u_{i,j} \in \Gamma$ indicates the table entry at row i and column j of the tabular version of ϕ. $|Q|$ and $|\Sigma|$ are the cardinalities of the set of states and the input alphabet, respectively.

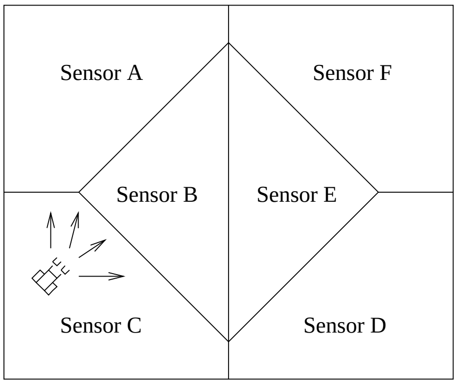

Figure 1: A robot wandering around a room

Behavior	**Sensor array data**
Wall following 1	CDFACDFACDFA
Wall following 2	CDFACDFACDFACDFA
Random walking 1	AEFFFDDFCAADBAAAE
	CCCCCCCCCCEACCAEC
	ADDEC
Random walking 2	CCAAAABBCFFEAADFE
	ACFBBFEACEDDDDDFF
	FFFFFFFFFFFBCFFEA
	ADDEFDECCEECCCAEC

Table 1: Robot movement data set

2.3 Environment

The proposed model was used explore the evolution of a lexicon describing robot behavior. Figure 1 shows a robot wandering in a room containing a distributed array of sensors. A robot activates the sensor in the area it occupies. Table 1 shows a data set that describes the movement of a robot at discrete time steps, kindly provided to us by Richard Brooks and David Friedlander. (See [13] for further details).

2.4 Measure of communicative success

The communicative success of agents was defined as the ability to imitate the communicative behavior of other agents. Let $a \in P$ be an agent and $S \subseteq P$ a non empty collection of agents. The communicative efficiency of a with respect to S and input string w, $E(a, S, w)$, is defined as

$$E(a, S, w) = \frac{\sum_{s \in S} e(a, s, w)}{|S|}$$

where $e(a, s, w) = 1$ if a and s produce the same

Parameter	Value
Simulation steps	1000–2000
Number of agents in P	128–512
Number of agents in S	4–32
Number of states in Q	4–16
Number of symbols in Σ	6
Number of symbols in Γ	4–16
Recombination probability p_r	0.6–0.7
Mutation probability p_m	0.001–0.01

Table 2: Parameters for simulations

output symbol u in response to input w, and 0 otherwise; $|S|$ is the cardinality of S. The generalization of this measure to a collection of perceptions W, $E(a, S, W)$, is straightforward.

Experiments were conducted to investigate whether a population of imitative agents perceiving the above environment is likely to arrive to a shared lexicon describing robot behavior. The conducted simulations are described by the following algorithm:

1. Create an initial random population P of agents
2. `Do until` number simulation steps N is met
   (a) `For each` agent $a \in P$ `do`
      i. Select a subpopulation $S \subseteq P$ of agents at random
      ii. Measure the imitative success $E(a, S, W)$ for a set of perceptions W

      `End for`

   (b) Select two individuals $a_1 \in P$ and $a_2 \in P$ for reproduction based on their communicative efficiency
   (c) Produce an offspring a_{new} from a_1 and a_2 using one-point recombination and point mutation, with probabilities p_r and p_m, respectively
   (d) Select a random individual $a_{old} \in P$
   (e) Replace a_{old} by a_{new}

   `End do`

3 Results

Several simulations were conducted using different combinations of parameter values as shown in table 3. The following were the major results:

1. Agents arrived to a shared lexicon describing robot behavior. However, simulations showed that there exists a threshold condition on the number of interactions required to achieve convergence in communication. Figure 2 shows the results of the simulations for different sizes of S at the proximity of the threshold value.

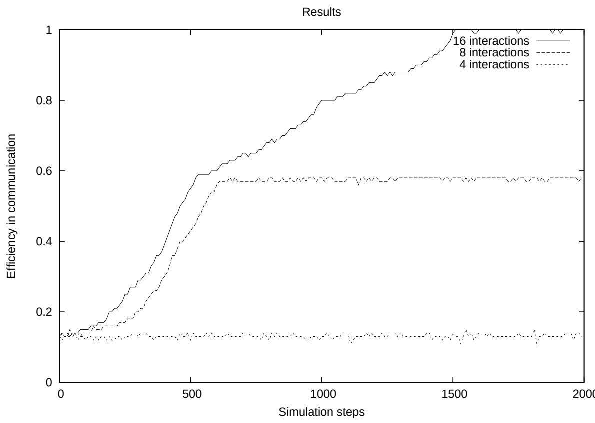

Figure 2: Simulation results

Behavior	Output
Wall following 1	`D`
Wall following 2	`D`
Random walking 1	`B`
Random walking 2	`B`

Table 3: Results

2. The same communicative behavior of the agents was achieved by means of several different machines. In general, results showed that machine convergence is not a necessary condition for convergence in communication.

3. Agents produced a meaningful emergent categorization of robot behaviors. Moreover, agents produce a meaningful generalization of perceptions when providing them with additional inputs. Table 2 shows the lexicon evolved in a typical simulation.

4. The communicative behavior of agents is produced by compact machines. In general, agents prefer machines with fewer states than the maximum number of states allowed in the simulations.

4 Discussion

The overall results indicate that given a sufficient number of interactions, a community of imitating agents is capable of evolving a shared lexicon describing robot behavior. Surprisingly, a meaningful categorization of perceptions emerges as a side effect of the imitative interaction of agents. Moreover, the use of FSTs allow agents to perceive a potentially infinite number of inputs and to capture regularities in perceptions.

4.1 Why imitation works

From the evolutionary perspective, how good is imitation for evolving a shared lexicon? Could an alternative communicative strategy invade a population of imitating agents?

Maynard-Smith[14] has demostrated that game theory can be used as a framework to explain the evolution of most phenotypic traits in situations in which fitness of a trait depend on what others are doing. He has also provided the notion of evolutionary stable strategy (ESS). An ESS is a phenotype such that, if almost all individuals have that phenotype, no alternative phenotype can invade the population.

In our model, success in imitation depends on the particular utterances produced by others. Furthermore, we have verified that imitation is an ESS in our model. However, further research is required to investigate the conditions under which imitation would fail. Previous studies have provided some insights [15][7].

4.2 Why categorization emerges

In general, experimental results showed that there is an evolutionary preference for agents which underlying FSTs have fewer states. These machines can capture regularities of inputs in an efficient way. Moreover, previous studies on language evolution have suggested a plausible relationship between compression and generalization in language evolution [16].

However, finite state machines can not capture all interesting robot behaviors in our model. In effect, it is theoretically imposible to learn any arbitrary class of languages [17]. Nevertheless, we believe that the consideration of more powerful computational models, (e.g. Push-down automata), will allow us to capture less restricted and more interesting patterns of robot behavior.

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