Evolution of Communication between Genetic Agents

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Abstract. We studied how communication evolves in a genetic based *Multi-Agent System* using an *Adapted Pittsburgh style Classifier System*. This work is an extension of a *Minimal Model of Communication* which consists in making two agents communicating through a medium of communication and playing a naming game with a limited number of situations to recognize. We complexify that model by increasing both the number of agents within the Multi-Agent System and the number of words that can be used by agents.

1 Introduction

Distributed artificial intelligence breaks complex problems into simplest ones. This decomposition into a multi-agent system involves that each agent is able to share its knowledge with the community. In our context, agents are *classifier systems* [1] that use a *genetic algorithms* [2] for their evolution. In order to solve a complex task, exchanging information becomes the main difficulty to clear up. When agents solve a problem in an heterogeneous context they need sometimes to know what the agent next to them perceives. This can be achieved by playing a naming game that consists in guessing what the communicating agent means by the word he emitted through a medium of communication [3]. We propose in this paper to extend this minimal model by increasing the number of agents communicating. The purpose here is to define how communication evolves when multi-agent complexity grows. We also increased the size of the lexicon they use in order to observe how environmental complexity influences the evolution of communication.

2 The Adapted Pittsburgh-style classifier system

The original framework of Holland was to create tools having the ability to solve problems learning potential solutions from simulation using a payoff function. Smith proposed a fully genetic algorithm based system: the Pittsburgh style classifier system (Pitt-CS) [4].

Such systems are filled with production rules called *classifiers*. The condition part of such rules reads the environment signal and the action part acts on the environment. Usually, the condition part is defined upon a ternary alphabet $\{0, 1, \#\}$, where $\#$, a *wildcard*, replaces 0 or 1. The action part contains only bits. A Pitt-CS works on a population of individuals wich are composed of classifiers. In other words, an individual is a set of classifiers also called as *knowledge structure*. The first population is generated using four parameters: a fixed number of individuals in population, a varying number of classifiers per individual (which is fixed in our adapted version), a fixed bit size for all classifiers, an allelic probability of having a wildcard in the condition part. Individuals are rewarded thanks to a multi-objective fitness function. Thus, individuals have a strength that globally reflects the strength of the classifiers filling it.

The use of a Genetic Algorithm is essential to a Pitt-CS: it is the learning and the evolution mechanism. Genetic algorithm applies its three main operators among individuals of the population using their fitness. It first *selects* parents that will eventually reproduce using *crossover* and *mutation* operators to create new offspring.

3 A minimal model of communication

3.1 Basic principles of the minimal model

To study how communication evolves, we just forced two agents to communicate one with the other [3]. Each agent has a ”view” of the world around it, i.e. it knows its own local environment. It is unable to see other agent’s local environment but needs this information to solve its part of the problem. Thus communication is the only way for agents to know things they cannot ”see”. Figure 1 describes a step by step example illustrating the evaluation mechanism:

1. The agent A1 chooses one classifier among available classifiers in the individual being evaluated. Then it posts the corresponding word (11) in the global environment. In its lexicon, 11 means that its local environment is 01. (bits 3 and 4 of its condition part)
2. The agent A2 reads the word from the global environment and chooses a classifier to activate within the individual being evaluated. This choice is realised looking for a classifier whose two first bits matches the global environment. If several classifiers match, the first of the more specialised ones will be chosen.
3. The agent A2 deduces that when A1 ”says” 11, this means that its local environment is 01. (the two last bits of the action part). Both agents understood each other : they will be rewarded.

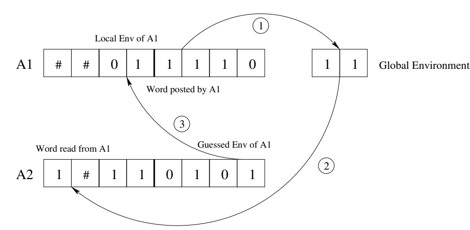

Figure 1. A step by step communication example.

3.2 Measurements and experiments

The fitness of individuals is computed from the number of times that two agents understand each other. We used results of the theory of communication [5] to analyse the establishment of a common referent i.e. *lexicon matrix*, between both agents. MacLennan [6] chooses

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the entropy as a measure of the dispersion of the denotation (i.e. lexicon) matrix:

$$H = -\sum_{i,j} p_{ij}\ log_2(p_{ij}) \ \text{ with } \ p_{ij} = \frac{M_{ij}}{\sum_{k,l} M_{kl}} \tag{1}$$

We adapted the measure so that it takes into account pairs of the denotation matrix belonging to the same row and the same column:

$$p_{ij} = \frac{M_{ij}}{\sum_k M_{kj} + \sum_l M_{il} - M_{ij}} \tag{2}$$

with M_{ij} the element of row i and column j of the denotation matrix.

To compare results, we used the *communication success rate* based on H_{Max} and H_{Min} the maximal and minimal possible dispersions:

$$Comm\_S = \frac{H_{Max} - H}{H_{Max} - H_{Min}} \times 100 \tag{3}$$

We experimented in different ways this minimal model including an application with simulated robots [3].

4 Extending Model

The minimal model of communication needs to be extended in order to study its main properties. We thus decide to study the evolution of communication when both the number of agents and the lexicon matrix size increase. The lexicon matrix will be kept square for this study. Thus, the number of words and local environments is called m and is related to the number of bits n of each classifier part: $m = 2^n$

Table 1 contains a brief reminder of the experimentation settings.

Parameter name	*Setting*
Agents number	from 2 to 10
Number of bits n per word/local environment	from 3 to 5
Individuals number	10
Number of classifier per individual	12
Number of Trials	20
$P_{\#}$	0%
$P_{Crossover}$	70%
$P_{Mutation}$	$0,1\%$
Elitism	20%
Selection mechanism	Roulette wheel

Table 1. Multi-agent system and G.A. settings.

We average results upon 100 experimentations of 5000 generations with different random seeds.

We first made an experimentation with $m = 3$. Whatever the number of agents, the communication rate reaches its maximum (more than 96%) upon generation 44. We then observe a progressive break down. The communication rate finally stabilizes around 65% at the end of the evolution. This rate indicates that communication occurs even if there are confusions [7].

We made a second experimentation with $m = 32$. Results are presented in figure 2. The plots indicate that the highest the number of agents is in the multi-agent system, the more communication success is high. The two extremes are the two agents curve and the 10 agents curve. The two agents plot reaches its maximum at generation 675 with 95,91% and then slightly decreases to 88,25% at the end of evolution. The 10 agents plot reaches its maximum at generation 406 with 99,29% and stabilize around 98,53% at the end of evolution. Those results seems also counter-intuitive. In fact, we have reached the cognitive limits that can handle an agent represented by a classifier systems with 10 individuals containing 12 classifiers [8].

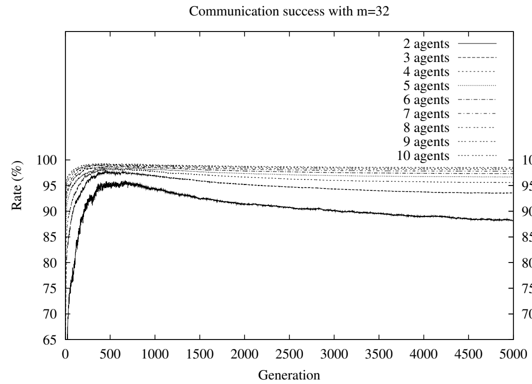

Figure 2. Results with m=32 (n=5)

5 Conclusion

Experiments we made show that confusion occurs in communication because there is at the same time too much and too little available words/local environments. The number of classifiers per individual explains the results we obtained. The biggest confusion appears with $m = 8$. With 12 classifiers, more than 8 meanings/words are distinguished. Two lexicons formed at the same time, implying confusion during communication even if success happens. With $m = 32$, the system stabilizes its behavior by using all classifiers. Thus, agents cannot waste time to communicate with useless words/meanings. The order observed between multi-agent systems size can be explained by the fact that two agents have more abilities to use more than one lexicon than 10 agents have. Thus the more you have agents in a group, the more language unificates.

Those conclusions need to be verified thanks to a deeper lexicon analysis. To further study the evolution of communication we need to measure two phenomenon that may emerge in lexicon: *homonymy* and *synonymy*. This is the second step of the extension of the minimal model of communication.

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