Evolving communication in embodied agents: Theory, Methods, and Evaluation

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Abstract. In this chapter we introduce the area of research that attempts to study the evolution of communication in embodied agents through adaptive techniques, such us artificial evolution. More specifically, we illustrate the theoretical assumptions behind this type of research, we present the methods that can be used to realize embodied and communicating artificial agents, and we discuss the main research challenges and the criteria for evaluating progresses in this field.

1 Introduction

Attempts to study the emergence of communication in populations of evolving agents have been present since the very beginnings of Artificial Life - Adaptive Behavior research (Ackley and Littman, 1994; Cangelosi and Parisi, 1998; Di Paolo, 1997; Oliphant, 1996; Werner and Dyer, 1992). However, in the last few years the field has been raising increasing interest, probably because of a general tendency in these communities to move from simple, low level, abilities to more complex ones, and from individual to social behaviors (Clark and Grush, 1999; De Jaegher and Di Paolo, 2007; Lindblom and Ziemke, 2003; Mirolli and Parisi, ress). The aim of this chapter is to contribute to the development of this emerging field of research by clarifying its scope, its assumptions, its methods, and its evaluation criteria. The chapter is structured as follows. First, we present our view of the general framework and the theoretical assumptions under which this kind of research is done (Section 2). Then we describe the methods with which to address the topic of the emergence of communication in embodied agents, both in terms of the algorithms that seem more suitable for this endeavor and in terms of the general methodology for conducting the research (Section 3). Finally, we present a number of assessment criteria which can be used for monitoring the progress in the field (Section 4).

2 Theory

2.1 The General Framework: Embodied Cognition

The kind of research we are interested in here falls under the general framework known as Embodied Cognition (Brooks, 1990; Clark, 1997; Pfeifer and Scheier, 1999; Varela et al., 1991). This can be considered as a collection of different but related ideas that have challenged the classical Cognitive Science paradigm that tended to study intelligence as an abstract process, without taking into account the physical aspects of intelligent agents and their environments.

In contrast with this, the embodied cognition framework tends to stress that in order to understand behavior one must consider the importance of: (a) the environment in which the agent is situated (situatedness); (b) the details of an agent's body (embodiment); (c) the pragmatic, adaptive value of a given behavior (adaptivity). Since not all researchers within embodied cognition share the same view reagarding the correct interpretation of these three points and their relative importance for understanding behavior, we now briefly discuss our own view on each of the three ideas which we think underly the embodied cognition framework, and explore the their implications for research on the emergence of communication in embodied agent.

Situatedness. Situatedness refers to the fact that an agent's cognitive activity is always situated in an environment: it is the environment that provides both the context of the activity and the inputs to the agent; it is through the modification of the environment or of the relationships between the agent and the environment that the agent's activity takes place; and it is the effect of the agent's actions on the environment that determines the success or failure of the activity itself. Furthermore, the environment typically plays a fundamental role also in the problem's solution (Parisi et al., 1990; Scheier et al., 1998). In particular, the importance of taking into account sensory-motor interactions with the environment clearly reveals itself if we consider perception. While classical cognitive science tended to view perception as an atemporal, passive, and purely internal process, embodied cognitive science recognizes that the agent's actions are an intrinsic part of agent's perceptual processes (see Churchland et al., 1994; Cliff and Noble, 1997; Floreano et al., 2004; Noe, 2004; Nolfi and Marocco, 2002). For example, it has been shown that perceptual problems which appear extremely difficult to solve if we assume the agent to be passive, can be easily solved by an active agent which, by moving in the environment, can influence its own sensory states (Nolfi, 2002; Scheier et al., 1998). With respect to the modeling of the emergence of communication, this implies that the artificial agents should be situated in a physical environment, and that the parameters that regulate how the agents interact with the external environment and between each other should be subjected to an adaptive process.

Embodiment. Embodiment refers to the fact that the specific characteristics of an agent's body play an important role in the way the agent behaves and solve its problems (Chiel and Beer, 1997). Important characteristics of the body include the shape and size of the body, the agent's weight, and the number, kind, and position of sensors and actuators. Just to give some simple examples: the problem of reaching the leaves of a three-meter tall tree is trivial for a giraffe, difficult for a man, and utterly impossible to be solved by, say, a small wheeled robot, because of the very different embodiments of these three kinds of agents.

Furthermore, the problem is almost as trivial for a squirrel as for a giraffe, but clearly the ways the two animals solve the same problem are extremely different because they depend on the very different bodies of the two animals. In short, the specifics of the body of an agent not only constrain what the agent can do, but also provide opportunities for how to solve a given task. With respect to the synthetic modeling of behavior, and in particular to the design of communicating agents, the recognition of the importance of embodiment translates into a preference for robotic experiments, in which all the physical details of an agent's body must be specified and can play a role in agent's behavior, with respect to dis-embodied simulations in which physical details are abstracted away. Another fundamental aspect of animals' bodies is constituted by their control systems, i.e. their brains. Classical cognitive science was based on the software metaphor according to which intelligence is a matter of abstract algorithms whose implementation was considered irrelevant. This assumption has been challenged by connectionists who argued that the kind of control system that is responsible for an organism's behavior does indeed influence the way in which the problems are solved (Rumelhart et al., 1986). In particular, it is now quite clear that many of the important characteristics of the behavior shown by natural organisms, like robustness, generalization, graceful degradation, and the like, crucially depend on the physical characteristics of real brains: for example, on the fact that they are analogue devices that perform a large number of operationsin parallel. This implies that artificial control systems that share the critical characteristics of their natural conterpart, like artificial neural networks, should be preferred, in the synthetic modeling of the emergence of communication, with respect to other kinds of control systems that are less bio-mimetic, like production rules or look-up tables.

Adaptivity. Finally, the third and last crucial assumption is that a real understanding of behavior must always take into account its adaptive value. The basic idea is that cognition is not an abstract process of disinterested agents; rather, cognition is for action (Wilson, 2002), in the sense that organisms' behaviors subserve, more or less directly, the survival and reproduction of the organism itself. This assumption is at the base of most artificial life - adaptive behavior research. From the point of view of designing artificial communication systems, taking an adaptationist stance to behavior implies that one should build set-ups in which communication is not the only behavior that agents have to perform. Rather, communication should be studied as a means of subserving other non-communicative behaviors which have (or are assumed to have) an independent adaptive value. Only in this way one can study and understand how communicative and non-communicative behavior co-adapt and co-develop (Nolfi, 2005b).

The three points just described must be considered as general desiderata that, taken together, define a prototypical set-up of the kind of experiments in the emergence of communication in embodied agents we have in mind. Of course, each of the points we have discussed does not constitute a clear-cut dichotomy: rather, for each of the above-mentioned aspects, a continuum exists between set-ups in which that aspect plays a crucial role and those in which it is not present at all. On the other hand, these aspects represent crucial prerequisites for studying some of the most important issues in the evolution of communication. In particular, the use of agents that are embodied and situated represents a necessary condition for studying how signals and meanings originate and how they are grounded in agents sensory-motor experiences. Similarly, the adoption of an adaptive framework represents a crucial pre-requisite for studying the relation between behavioural, cognitive, and communicative skills (Nolfi, 2005b).

2.2 Communication as a Complex Adaptive System

Studying communication in embodied agents implies dealing with complex adaptive systems that involve a hierarchy of levels of organizations extending at different time scales (Keijzer, 2001; Nolfi, 2005a, ress). This has important implications with respect to the methods that can be used to develop communicating agents. In the next section we will discucss these methods, while in this section we will explain in what sense communication can be considered as an complex adaptive system.

The embodied cognition perspective just discussed implies that behavior is an emergent property resulting from the non-linear interactions between an agent's body, its brain, and the external environment, including the social environment, i.e. the other agents. At any point in time, the structure of the environment and the agent/environmental relation co-determine, together with the agent's control system, the bodily and motor reactions of the agent. In turn, these reactions co-determine how the environment itself and/or the agent/environmental relation vary. Sequences of these fine-grained interactions, occurring at a fast time rate, lead to an emergent property – behavior – that extends over a significant larger time span than the interactions from which it originates. Since the interactions between the agent's control system, its body, and the external environment have non-linear dynamics (meaning that small variations can lead to very different outcomes and, vice-versa, very different initial states can lead to very similar outcomes), the relation between the rules that govern these fine-grained interactions and the resulting behavior is very indirect and difficult to infer. This implies that the behavioral properties of a given agent-environment system can very hardly be predicted even if one possess a complete knowledge of all the interacting elements and of the rules governing the interactions.

Furthermore, behavior is a multi-scale phenomenon with different levels of organization and involving features occurring at different time scales. Agent/environmental interactions occurring at a rate of milliseconds lead to very simple behaviors that extend over a short time span (e.g. obstacle avoidance behaviors extending over hundreds milliseconds); in turn, interactions between these simple behaviors (e.g. obstacle avoidance and target approaching behaviors) can lead to more complex behaviors that extend over longer time spans (e.g. navigation behaviors extending over seconds or minutes). This process is recursive, with interactions occurring at lower levels of organization and extending over short time spans giving rise to behavioral properties at higher levels of organization. Furthermore, the processes occurring at higher levels of organization and extending over long time periods can on their turn affect the lower levels processes from which they originated (for more detailed discussions on this topic see Keijzer, 2001; Nolfi, 2005a, ress). The overall picture thus is that of a multi-scale phenomenon involving bottom-up and top-down relations between emergent properties occurring at different levels of organizations and at different time rates.

If this is true for individual behaviors, it is even more true for social behaviors. Indeed, social behaviours are the emergent result of a large number of concurrent interactions that include both the interactions between each agent and the physical environment and the interactions among agents. Thus, in the case of social behavior the complexities of social interactions add-up to the complexities of the interactions between the single agents and the environment. This, in turn, tends to lead to a complex system that includes a larger number of levels of organization with respect to what happens in non-social contexts. Indeed, in a social context, an external observer can typically distingush at least a level of individual behaviours and a level of the social behaviours that emerge from the interactions between the agents that are regulated by the individual behaviours. Both individual and social behavior might involve different levels of organization that extend to different time scales. And some higher-level social behaviors might include complex high-level properties that change at a very slow time rate and extend over very large time spans. Communication systems are indeed high level behavioral properties that extend over relatively long time span (i.e. which remain stable over long periods) and result from a large number of hierarchically organized and mutually interacting behavioural processes occurring at lower levels of organization. These lower-level behaviors that extend over shorter time spans might include communicative interactions between individuals (e.g. dance behaviors in bees), collective behaviors (e.g. cooperative behaviors or shared attention behaviors), and individuals behaviors (e.g. locomotion).

3 Method

3.1 Adaptive Methods for designing self-organizing communication systems

The complex adaptive nature of behavior and communication has important consequences with respect to the endeavor of designing embodied and communicating agents, and more specifically, with respect to the design methods which are more appropriate to this endeavor. In particular, it explains why methods based on explicit design are typically inadequate. In fact, as we have discussed in the previous section, it is very difficult if not utterly impossible to infer the high-level behavioral properties emerging from the fine-grained interactions between an agent and its environment and from the interactions between individual and social behaviors. This implies that designing (i.e. handcrafting) the sensory-motor rules that regulate the fine-grained interactions that lead to the desired communicative and non-communicative behaviors is in general extremely difficult. A more promising way to proceed consists in using design methods which are based on a self-organization process. In this methods the agent develop their skills autonomously, while interacting with their environment, on the basis of an evaluation of their overall performance. More specifically, the characteristics that regulate the fine-grained interactions between the agents and the environment are encoded in free parameters that are varied during the course of the adaptation process. The variation of the free parameters are retained or discarded on the basis of their effects at the level of the global behavior exhibited by the agents.

Three different adaptive methods — evolutionary algorithms, simulated annealing, and reinforcement learning — meet these general characteristics. We now briefly discuss them in turn.

3.1.1 Evolutionary algorithms. Evolutionary algorithms ((Back et al., 1991), (Fogel et al., 1966), (Koza, 1992), (Holland, 1975)) are the method most widely used to study the evolution of communication in embodied and situated agents. The application of evolutionary algorithms to the synthesis of embodied and situated agents is called 'Evolutionary Robotics' (Floreano et al., 2008; Nolfi and Floreano, 2000) and is typically realized through the following procedure. An initial population of different artificial genotypes, each encoding the control system (and eventually the morphology) of an agent, are created randomly. Each genotype is translated into a corresponding phenotype (i.e. into a corresponding robot) that is allowed to "live" (i.e. to move and interact with the external environment and with other agents) while its performance (fitness) with respect to a given task is automatically evaluated. Agents are placed in the environment and evaluated in groups that might be heterogeneous (i.e. might consist of agents with different characteristics corresponding to different genotypes) or homogeneous (i.e. might consist of agents with identical genotypes and control systems). Then, a new population is generated by allowing the genotypes of the fittest agents to reproduce by generating copies of themselves with the addition of changes introduced by some genetic operators (e.g., mutations, crossover, duplication). This process is repeated for a number of generations until the agents of the current generation satisfy the performance criterion (fitness function) set by the experimenter.

The characteristics which should be defined by the experimenter consist in: (1) the fitness function, i.e. the criterion used for automatically evaluating the performance of the agents with respect to the given task, and (2) the genotype-to-phenotype mapping, i.e. the way in which a genotype is translated in the corresponding phenotypical agents. In many cases, only some of the characteristics of the agents' phenotype are generated randomly and varied during the adaptive process, while the other characteristics are hand-designed and kept fixed. Furthermore, typically the genotype-to-phenotype mapping consists of a simple one-to-one mapping in which each part of the genotype (gene) encodes the characteristic of the corresponding phenotypical feature. In other cases, the genotype-to-phenotype mapping might involve a complex process in which the genotype regulates how an initial embryo grows and differentiate through processes loosely inspired by natural morphogenetic development. In this case, the experimenter has to design the rules that determine how the genotype regulates the developmental process. What is common to all cases is that the behavioural and communicative skills exhibited by the evolving agents and the way in which the agents manage to produce such skills are the result of the adaptive process and are not handcrafted by the experimenter.

For what concerns specifically the evolution of communication, evolutionary methods are attractive for at least three reasons. The first reason is that they provide a way to model the role that natural evolution might have had in the evolution of communication. The second reason is that they provide a way to allow the agents themselves to develop their communication skills autonomously by reducing the intervention of the experimenter to the minimum. The third reason is that they provide an easy and effective way to co-adapt different characteristics of the agents. In particular, they allow to co-evolve agents behavioural and communicative skills. These aspects will be illustrated through concrete examples in the following chapters.

3.1.2 Simulated annealing. Another algorithm suitable for designing self-organizing communication systems is Simulated Annealing. This is a probabilistic algorithm developed by Kirkpatrick and collegues (Kirkpatrick et al., 1983) and based on the Metropolis algorithm developed in statistical mechanics (Metropolis et al., 1953) (For a detailed introduction to the algorithm see van Laarhoven and Aarts (1987)). The name and inspiration of this algorithm do not come from an adaptive process observed in natural organisms but rather from the annealing technique of metallurgy, where a piece of metal or glass is repeatedly heated and cooled so to increase the size of its crystals and reduce their defects. The heating is done in order to make the atoms wander randomly through states of high energy and get them unstuck from their initial positions. The slow cooling increases the chances that the atoms find crystal configurations, which are the ones with lower internal energy.

In short, the adaptation process in this case is realized by introducing random perturbations in a single candidate solution and by retaining or discarding the perturbation introduced on the basis of their positive or negative effects with respect to a performance measure. More precisely, for every adaptive cycle, the original configuration of the free parameter is replaced with the new perturbed configuration with a probability that depends on the difference in performance between the two and on a parameter T (the temperature), which is gradually decreased during the process. In analogy with the metallurgic technique, the idea is that the solution changes almost randomly when T is high, while only changes guaranteeing an increase of performance are accepted as T goes to zero. The possibility to accept variations that produce a decrement of the performance is introduced in order to allow the algorithm to exit from local minima. The decrease of the temperature (and consequently of the probability that counter-adaptive variations are retained) is introduced so to permit the optimization of the solution during the last phases of the adaptive process. Simulated annealing can therefore be used to implement an adaptive process that operates on a single individual. However, it can also be applied to two or more individuals that adapt concurrently to their physical and social environment. For a preliminary attempt to apply this algorithm to the study of the evolution of communication, see Acerbi and Nolfi (2007).

3.1.3 Reinforcement learning. Still another class of adaptive algorithms that might allow the agents to develop their behavioural and communicative skills autonomously is constituted by reinforcement learning algorithms (for a detailed introduction to the field see Sutton and Barto, 1998). This class of algorithms derives its name and the basic idea from the psychological framework of reinforcement learning, which constituted the fundamental experimental paradigm of behaviorism. The idea is to have an agent that autonomously learns to behave so as to maximize its long-term rewards. These machine learning algorithms attempt to find the most effective *policy*, i.e. the most effective set of rules mapping the perceived states of the environment to the actions that the agent takes. The learning process is guided only by the reinforcements (which can be both positive and negative) reached by the agent. As usual, at the beginning the agent starts with random parameters defining a random policy and is placed in its environment. At each time step the agent perceives the current state of the environment trough its sensors and produces an action according to its policy. This action results in a new state and a (positive or negative) reward. Based on this reward the free parameters defining the policy are changed so to maximize the expected rewards.

Typically, the environment is formulated as a grid, states and actions are discrete and of finite number, and the policy is represented by a function that maps each state to the distribution of probabilities of taking each of the possible actions. However, reinforcement learning algorithms can also be applied to cases involving continuous state and action spaces (see, for example, Doya, 2000). This makes this kind of algorithm suitable for embodied cognition research. Indeed, reiforcement learning has been used to develop robots that acquire their skill autonomously in interaction with the environment (see, for example, Peters and Schaal, 2008a,b; Wiering, 1999). On the other hand, the use of this kind of technique for developing communication systems is still to be explored. In particular, it is far from clear whether reinforcement learning algorithms might be suitable for a population of autonomous agents that should develop behavioral and communicative skills *without the need to directly reinforce communicative interactions*, which is an important tenet of research on embodied and communicating agents (see the previous section). Another possibility to explore is to use reinforcement learning algorithms in social learning contexts by using communicative signals as the reinforcers for social learning.

3.2 Research Methodology

While in the first part of the present section we have described the most suitable algorithms for developing embodied and communicating agents, we now describe the general methodology which is typically adopted in this kind of research. This methodology involves the following steps:

1. Formulating a question or a hypothesis on the origin of communication or on some aspect of communication to be investigated.
2. Defining an experimental setup to address the question or to test the hypothesis. This requires defining the following aspects:
   (a) The task to be solved by a group of agents and the characteristics of the environment in which the agents are situated. The chosen task/environment should create an adaptive pressure toward the development of coordinated and/or cooperative skills which in turn might constitute the adaptive basis for the development of communication skills. The definition of the task/environment should then be operationalized by defining the detailed characteristics of the physical environment and the evaluation criteria (i.e. fitness function, performance measure, or reward criteria) used to evaluate the extent to which the agents are able to solve the given problem. However, the evaluation criteria should not score the agents directly for their ability to communicate. The introduction of an explicit reward for communicating, in fact, will prevent the experimenter from the possibility to study the conditions in which communication emerge and the relation between the development of behavioural and communicative skills. Moreover, it will not leave the agents free to determine the characteristics of the communication system to be developed (Nolfi, 2005b).
   (b) The characteristics of the agents that are encoded in free parameters and subjected to the adaptive process and those that are fixed and predetermined by the experimenter. The selection of the characteristics to be included in free parameters should be made so as to allow the evolutionary process to shape agents' individual and social/communicative behaviors within a large variety of possible alternatives. The characteristics of the agents which are pre-determined and fixed, on the other hand, should be chosen so to provide the elements which are necessary for communication to emerge (e.g. the possibility to produce and detect signals) while limiting as much as possible the constraints imposed on the adaptive agents.
   (c) The type and the detailed characteristics of the adaptive algorithm to use (e.g. the rate with which variations are introduced, or the probability that determines whether a certain variation or group of variations is retained or discarded).
3. Developing the necessary hardware and software tools for running the experiments in simulation and/or in hardware and running the experiments themselves.
4. Analyzing the results obtained at the end of the adaptive process and during the course of the process itself at different levels of description (e.g. at the level of performance, at the level of the motor and communicative behaviours exhibited by the agents, at the level of the phenotypes and/or of the genotypes).

5. Assessing the significance of the obtained results with respect to the hypothesis formulated at the beginning of the research and/or with respect to the implications of the results on the development of effective methods for building embodied and communicating agents.

Concerning the first point, there are many open issues in the emergence of communication which can be addressed with this methodology, including: the identification of the adaptive conditions that lead to the emergence of communication, the factors that influences the stability, roboustness, and evolvability of the evolved communication systems, the relation between implicit and explicit communication, the characteristics of the evolved communication system, the extent to which the communication system can complexify, the relationship between communicative and non communicative behaviors, etc. A more detailed analysis of the various issues that can be addressed in research on the emergence of communication will be given in the following section.

With respect to the experimental set-up, most of the research on embodied and communicating agents has been focusing on real or simulated wheeled robots, controlled by artificial neural networks evolved for solving cooperative or coordinated tasks. However, nothing prevents this kind of research to be applied to other set-ups: for example to set-ups involving bio-mimetic robots provided with bodies and a sensory-systems that closely match those of a specific natural species and that are placed in an environment which matches the corresponding species niche.

4 Evaluation criteria

There are several dimensions along which progress can be made in research on the evolution of communication in embodied agents. What follows is a list of some of the most important dimensions (including, where appropriate, relative sub-dimensions), and a description of how progress can be assessed for each dimension.

4.1 Adaptive role

A first important criterion for evaluating progress in this research is to identify whether a population of initially non-communicating agents is able to develop a communication system or not, and the extent to which communication enhances agents' adaptive capabilities. One straightforward way to verify whether agents are able to develop adaptive communication capabilities and to identify the extent to which communication enhances agents' overall performance is to compare the performance achieved in standard and in control experiments in which agents are or are not allowed to communicate, respectively. This simple method, however, can only be used when agents communicate through dedicated communication channels that can be selectively disabled or impaired. In the other cases, i.e., in the cases in which the same sensory modalities provide both information about the physical and social environment and about other agents' signalling behaviors (e.g. Quinn, 2001; Quinn et al., 2003), the identification of whether a communication system has been developed or not and the evaluation of the adaptive value of such a communication system necessarily requires more complex analysis in which the detailed characteristics of the communication system and of their specific adaptive contribution are identified (see below).

4.2 Expressive power and organizational complexity

A second important dimension concerns the evaluation of the expressive power and of the organizational complexity of the communication system. This aspect can be measured along several sub-dimensions:

4.2.1 Number of signals. In contrast with human language, animal communication systems have a very limited set of signals. Though we do not have precise estimations, the repertoire of several animal communication systems seems to reach something like 20-30 signals (see, for example, Smith, 1977). In systems of this sort, the number of signals strongly correlates with the expressive power of the communication system which, in turn, correlates with the potential adaptive role of communication. Pioneering research in the evolution of animal-like forms of communication concerns experiments involving communication systems based on only 1-2 different signals (e.g., Cangelosi and Parisi, 1998). Hence, substantial progress can be made in this respect.

4.2.2 Type of signals. The nature of signals can be categorized along several dimensions:

- emotional/motivational versus referential (Lancaster, 1968; Marler et al., 1992), i.e., signals that provide information about the emotional-motivational state of sender versus signals that provide information about the state of the external environment;
- deictic versus displaced, i.e., signals that provide referential information that is dependent or independent, respectively, on the current context experienced by the sender or by the receiver (Hockett, 1960);
- non-abstract versus abstract (Hauser, 1998, 1996; Rendall et al., 1999), i.e., signals that provide information about regularities that are directly and currently available to the agents emitting the signals versus signals that encode information that is not directly available and that has been generated by integrating sensory-motor information over time;
- relational versus informative/manipulative signals, i.e., signals used to create and maintain certain social relationships between individuals and in which the roles of the individuals involved in communication cannot be distinguished, versus signals that convey information possessed by the individual that emits the signal to the individual that receives the signal or in which

the former individual manipulates the latter, i.e. in which the signal alters the behaviour of the receiver in a way that is advantageous for the emitter.

The vast majority of communication acts in animals concerns simple communication forms that convey information that is emotional-motivational, deictic, and that has a low level of abstraction (e.g., 'I am hungry, here and now'). However, in some cases, animals also display more complex forms of communication that are referential (e.g., the alarm calls of vervet monkeys, see Seyfarth et al., 1980), displaced (e.g., the information on food sources conveyed by honeybees through their dance Frisch, 1967), and abstract.

Pioneering research in the evolution of animal communication typically involves signals conveying information that is deictic and that can be extracted on the basis of the currently available sensory states (e.g. Cangelosi and Parisi, 1998). The development of new experimental settings and new models that can lead to the emergence of displaced signals would represent a clear progress with respect to the state of the art. Similarly, progress can be made by devising agents able to extract relevant information to be communicated by integrating sensory-motor states through time, and/or by producing behaviors that allow agents to gather the relevant information from the environment, and/or by generating the required information through social-communicative interactions.

Other important progress can be made by developing artificial agents able to use different forms of communication based on different types of signals (i.e., relational, informational, and manipulative), depending on the circumstances.

4.2.3 Protocol regulating signaling behaviors. In addition to the two aspects discussed above, a communication system is characterized by a protocol, i.e. by a set of rules that regulate when and how signals are exchanged between agents. Forms of communication might range from simple continuous broadcasted signalling to complex regulated communication protocols in which agents, for example, signal in the presence of potential receivers only, take turns, and use different communication protocols in functionally different circumstances. The communication protocol plays a key role in determining the adaptive value of a communication system (see for example, Marocco and Nolfi, 2007; Trianni and Dorigo, 2006).

In pioneering research on the evolution of communication, the communication protocol is extremely simple and is often hand-crafted by the experimenter and fixed (see Kirby, 2002; Wagner et al., 2003). Therefore, the development of embodied and communicating agents in which the communication protocol and the communication systems are co-adapted and in which agents are able to switch between different communication protocols on the fly represents an important progress in this research area.

4.2.4 Signal structure. The level of structuredness in a given communication system can be seen as a continuum. At one end, there are completely unstructured communication systems, which seem to form the vast majority of animal communication. Then there are 'syntactic' communication systems in which meaningful signals are produced by (sometimes very complex) sequences of minimal meaningless units (there is ample evidence that this minimal form of syntax is present in the communication systems of birds and several non-human primates, see, for example, Hauser, 1996). An even more complex form of structuredness is compositionality, that is, the possibility to combine meaningful signals to convey complex meaning (so far, there seems to be no evidence of compositionality in natural animal communication systems, but linguistically trained great apes have been shown to be capable of producing compositional utterances). Finally, at the other extreme of structural complexity, we have full-blown human language, in which utterances are not only composed of meaningful signals, but this composition is also regulated by grammatical rules (there is no evidence of grammar in natural animal communication, but several linguistically trained animals including parrots, dolphins and great apes have demonstrated to understand some forms of grammar: see, for example, Kako, 1999). The possibility to create embodied agents that are able to develop structured forms of communication from scratch has not been successfully tackled yet and represents an extremely challenging task. As far as we know, in fact, in the existing works involving embodied agents displaying some form of structured communication (e.g. Cangelosi, 2001; Sugita and Tani, 2005), the structure is built in the communication system by the researcher, and does not emerge through a self-organization process (Wagner et al., 2003). Therefore, even preliminary progress along this dimension would represent an important achievement for this field of research.

4.3 Stability, robustness, and Evolvability

Other criteria for measuring progress in this type of research concern the level of stability, robustness, and evolvability of emerged communication systems.

With the expression 'stability of the communication system' we refer to the ability of a population of communicating agents to preserve the functionality of their communication system during the adaptation process. In fact, the functionality of the communication system can be preserved while the produced signals and/or the effect of the signals and/or the communication protocol vary. Stability is particularly important in experiments in which selection operates at the level of individuals rather than at the level of the group. In the former case, in fact, the conflict of interest between individuals might prevent the preservation of communicative behaviors that provide an advantage only for part of the communicating individuals.

Robustness refers to the ability to cope with agents' internal, environmental, and social variations so as to preserve agents' adaptive skills. Moreover, it refers to the ability to cope with noise in the communication channel and other unpredictable events that might affect agents' interactions with the physical and social environment (e.g., the availability or not of other agents that might communicate the relevant information).

Evolvability refers to two different aspects. The first aspect concerns the identification of the mechanisms that can overcome or counterbalance the difficulties originating from the fact that the emergence of a communication system requires the development of two separate abilities (i.e., an ability to produce useful signals and an ability to appropriately react to these signals) that might not provide an adaptive advantage in isolation (Maynard-Smith and Harper, 2003; Mirolli and Parisi, 2008). The second aspect concerns the identification of characteristics and/or mechanisms that can lead to an open-ended evolutionary process in which the population does not quickly converge on a stable solution but rather keeps changing so to display progressively better performance and, possibly, more and more complex forms of communication.

4.4 Knowledge gain (modeling)

Last but not least, research in this field may lead to progress from the point of view of understanding how communication evolved in the biological world and from the point of view of identifying the key mechanisms that regulate animal communication. Progress in this respect would consist in the development of new theories or original hypotheses that might later be verified experimentally or in the synthesis of simulation data that might confirm or disconfirm existing theories.

5 Summary and conclusion

In this chapter we have provided a brief introduction to the study of the evolution of communication in embodied agents. More specifically, we have described: (1) the general theoretical framework that underlies research in this area, (2) a suitable methodology for conducting experimental research, and (3) a series of dimensions along which research progress can be evaluated.

In the next four chapters of this section we will describe concrete examples of research on the emergence of communication in embodied agents which address some of the issues discussed above. Finally, in the concluding chapter of this part, we will briefly illustrate the state of the art and the issues that still represent open challenges together with the most promising research directions for future work in this area.

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