Embodied Autonomy in Digital Ecosystems: From Bio-inspired Agents to Cognitive Systems

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Abstract

This paper proposes to promote autonomy in digital ecosystems so that it provides agents with information to improve the behavior of the digital ecosystem in terms of stability. This work proposes that, in digital ecosystems, autonomous agents can provide fundamental services and information. The final goal is to run the ecosystem, generate novel conditions and let agents exploit them. A set of evaluation measures must be defined as well. We want to provide an outline of some global indicators, such as heterogeneity and diversity, and establish relationships between agent behavior and these global indicators to fully understand interactions between agents, and to understand the dependence and autonomy relations that emerge between the interacting agents. Individual variations, interaction dependencies, and environmental factors are determinants of autonomy that would be considered. The paper concludes with a discussion of situations when autonomy is a milestone.

1. Introduction

One of the main challenges in current applications of multi-agent technologies in relation with human operators or users is how to ensure a coherent behavior of the system without limiting the autonomy of the agents within. Addressing this issue needs a global study of what could be the rights and duties of agents in such systems and how to balance both while preserving the autonomy of the agents and the prerogatives of the human operators or users.

As far as agents are concerned, a lot of work has been done in the areas of models, frameworks, coordination languages and protocols, planning and decision algorithms. Therefore agents are provided with tools they use to coordinate their activities, but hardly to decide themselves on what they should do, especially in contexts of mixed initiative with human operators or users. For instance, organizational structures, norms, institutions or constraints are imposed to agents in an attempt to achieve the desired functioning of the system.

What at the system level is perceived as an attempt to achieve order in some sense may be considered at the agents' level to be a control on their autonomy. Autonomy is one of the salient features of multi-agent systems and defining and identifying agent autonomy is an active area of research in the multi-agent community. Many architectures and models for autonomous agents have been proposed to enable agents to reason about their rights and duties, to comply with different constraints, to abide by regulations or procedures, to behave consistently, to cooperate with other (artificial or human) agents... so that unwanted or hazardous situations should be avoided.

Consequently distributed control mechanisms have to be designed to define what agents' autonomy should be, i.e. what the agents should do and may do. In a general sense, these rights and duties involve concepts such as norms, standards, task and authority sharing between artificial and human agents, conflict detection and solving, collective performance. The issue also concerns the strategies for shifting the initiative and distributed control between agents and from agents to the human beings and conversely, including proactive behaviors. Deciding who should do what and when is a complex problem that depends not only on the skills of the participants, but also on the current context (health of the system, set of tasks to be performed, time pressure).

This is of particular interest for authority sharing between robots (e.g. UAVs, UGVs) or automatisms (e.g. autopilots) and human operators, social robotics (e.g. robot assistance to disabled people), ambient intelligence, web agents, e-commerce, interactive games.

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As far as open systems are concerned, social order is even more difficult to achieve as it is impossible to make assumptions on the agents' internal models, as they could have been designed by third-parties.

According to the Agent Link's Roadmap [1], Virtual Organisation formation and management is a challenge. Virtual Organisations (VOs) have been identified as the means to release the power of the Grid, but well-defined procedures for determining when to form new VOs, how to manage them, and ultimately how and when to disband them, are still missing. Working with complex data in dynamic environments, as it is the case of the automation of coalition or virtual organizations formations to create a dynamic packaging that requires of taking many decisions in very short time to take advantage of the business opportunities that appear through time, with the expectancy to be the first or the winner of every single deal at a short term, and gaining business and, at a long term, be more profitable. Taking into account that all Artificial Intelligence (AI) systems share a few characteristics: they are designed to work with data sets that are large, complex, or both; to search through them and find relevant data; and to look for patterns. AI systems are useful for dealing with any dynamic environment in which they have to make intelligent choices, depending upon the input, among a number of possible answers. They also use samples to form generalizations about an entire data set and, in some cases, make or help make intelligent decisions. Potentially, they could even execute tasks.

Numerical analytics systems find patterns and rules in big numerical data sets. They are most useful for problems (such as the detection of fraud) that require heavy number crunching to distinguish among different sets of items. Rule-based decision systems use predetermined rules or logic, with or without numerical data, to make decisions and determine outcomes. They are useful for automating work flows. Autonomous execution systems (also known as agents or bots), which run continuously, monitor information as it arrives—typically from several distributed sites—and execute specific tasks in response to what they find. These systems are most useful for automating tasks across organizations by using data shared over the Internet, especially when the underlying data are structured according to prevailing standards such as the Extensible Mark-up Language (XML). The development of machine-readable Internet content based on XML, which has spawned the use of agent or bot technologies, makes it possible to improve a company's information-exchange capabilities to an unprecedented extent. Among other possibilities, this development means that businesses can automate interactions with their partners up and down the value chain.

Although these applications of AI are promising, the technology is not right for all information problems. First, it is overkill for simple questions and not sophisticated enough—yet—for some complex ones. Second, since many AI solutions improve performance through trial and error, AI is not a good choice for mission-critical challenges. However, there are still some questions: Are the business processes and technologies of the company or the virtual organization sufficiently standardized for it to apply AI? In general, AI-based tools are most effective when business processes and decision logic are consistent and can be encoded; furthermore, the technology infrastructure must capture, in a timely and accurate way, the data the AI system requires. Nonetheless, even organizations without standardized process and technology infrastructures can apply AI-based tools to isolated problems. What parts of the business are best suited to AI? The virtual organizations identify activities that are complex, repetitive, information based—and not mission critical. In those areas, basic AI technologies can often be deployed in parallel with existing approaches and then iteratively refined and allowed to take over more and more of the total activity.

2. Digital ecosystems

This paper introduces a viewpoint to evaluate heterogeneity in Multi-Agent Systems (MAS) that interact to create dynamic packaging and virtual organizations. The need to measure heterogeneity or diversity is key concept to stabilize ecosystems of companies with dynamic deals. The main causes of instability that nowadays are foreseen are: imperfect data (lack of data, bad data, wrong data, delayed data, distorted data, etc), dynamic market (chaotic changing demand, and increasing competition), and finally the lack of appropriate electronic institutions and knowledge derived from immature technologies that do not help designers nor managers design automatic systems that help dynamic packaging nor virtual organizations.

The term Digital Ecosystem (DE) has been used to describe a variety of concepts. However, perhaps the most frequent references to Digital Ecosystems arise in Artificial Life research. A digital ecosystem is a loosely coupled, domain clustered, demand driven collaborative system with an environment where each digital (agent) species is proactive and responsive for its own benefit or profit. It is a self-organized infrastructure with emergent properties aimed at creating an open environment for networked organizations or agents.

The focus of our approach is on the autonomy of these systems, namely populated by intelligent agents, who inherit all the problems mentioned above. Their interactions will be grounded in an ecosystem of agents, where agents will be self-organised. One important question to analyse these Digital Ecosystems is *the inclusion of interactions of the agents*. The interactions always exist as for example, the agents that trade in electronic commerce have to manage finally the negotiation for product delivery to the person or institution that these agents represent.

3. Open negotiation environment in digital business ecosystems: the nature-inspired computing

In the framework of Digital Business Ecosystems, (DBE), an EU IST FP 6 integrated project investigating the design of a digital business ecosystem, which is the enabling technology for the Business Ecosystem; the Open Negotiation Environment (ONE) project allows organizations to create contract agreements in order to supply complex, integrated services as a virtual organization (or coalition). The ONE project is a STREP project funded by the European Commission under the DG-INFSO that is geared towards SME's in order to provide them with a trusted, secure and free of charge technological environment in which they are able to create tactical and strategic alliances; for the ultimate goal of pursuing business opportunities and growth.

An Open Negotiation Environment is defined as evolutionary self-organising system aimed at creating a digital software environment for small (virtual) organisations that support the regional and local development by empowering open, distributed and adaptive technologies and evolutionary business models for small organisations growth. An open-source distributed environment will support the spontaneous evolution, adaptation and composition of agent communities.

This involves taking ideas, concepts, and designs from biology and applying them to computing. In engineering terms, this would be described as discovering biological design modules [2] to be used in computer systems. In computing, the best known example would be Evolutionary Computing, where the concepts of evolutionary theory are used to solve optimisation problems, including: Agent-based modelling of complex systems; Novel forms of distributed evolutionary computing for solving optimisation problems; and Neural networks, which can be used to provide a learning-based intelligence which is suitable for a wide variety of applications.

The next step would be to develop Biological Design Modules from ecological and biological systems, and adapt their application in software engineering. The ultimate goal would be to create a reference library of Biological Design Modules which could be used in computing. So, the first step will be to identify the characteristics of biological modularity that are applicable to computing.

4. Agent autonomy

We adopt the general approach developed in [3], [4] (for a general view see [5]). Agent orientation refers to a software development perspective that has evolved in the past 25 years in the fields of agents and multi-agent systems. The basic notion underlying this perspective is that of an agent, that is, an entity whose behavior deserves to be called flexible, social, and autonomous. As an autonomous entity, an agent possesses action choice and is at least to some extent capable of deciding and acting under self-control. Through its emphasis on autonomy, agent orientation significantly differs from traditional engineering perspectives such as structure orientation or object orientation. These perspectives are targeted on the development of systems whose behavior is fully determined and controlled by external units (e.g., by a programmer at design time and/or a user at run time), and thus inherently fail to capture the notion of autonomy.

The simplest notion of autonomy is that of local determination. An agent that determines its actions for itself based only on its internal state is generally considered autonomous, that is, if the determination of the agent's behavior is local and without input from other agents, the agent is autonomous. Thus, a reactive agent running on a deterministic program would be considered autonomous, but since such an agent has no intentions, and is incapable of introspection, autonomy seems to be a concept of limited usefulness in the context of strictly reactive agents. In contrast, other investigators in the area of autonomy claim that the concept of autonomy is appropriate only for intentional agents that have introspective abilities. An intermediate position is that autonomy is essentially a social notion, which can be understood in terms of social dependencies.

One aspect of autonomy we could explore is individual variation among agents such as agent behavior, decision patterns as same as human personality [6]. Autonomy is partly a behavioral characteristic, and thus varies across agents according to individual characteristics. There are individual agents who lead and others who prefer to follow. Another aspect of autonomy to be considered is inter-individual dependencies such as dependencies in the physical world and inter-individual social dependencies. Earlier papers, e.g. [7] have claimed that autonomy can be fully understood in terms of social independence. While this notion of autonomy is satisfactory for simple agents, it becomes inadequate as agents become more richly endowed with psychological characteristics, in particular, when agents can be considered to have individuality. A third area of exploration is social regulation and an agent's attitude toward laws, norms, and values in the agent's environment such as found in agent organizations, institutions, and general agent society.

5. Environment and autonomy

It is common to refer to individual agents that determine their behavior without the influence of other individual agents as autonomous. This reflects the notion that an autonomous agent is independent and self-X stance. These, however, are vague notions. What is generally meant is that an autonomous agent is empowered to choose to act contrary to the desires of other individual agents. Consider two simple individual agents each of which must make a choice between two options P and Q. The first could make the decision based on input from a sensor monitoring some physical condition of the individual agent's environment. The second could make the decision based on input from another individual agent. The first individual agent acts independently of any other individual agent, but the second individual agent's action is dependent on the action of another individual agent. The first is autonomous with respect to the decision, but the second is not autonomous according to common notions. Is there any meaningful distinction between these individual agents? Both are reacting to the condition of an input. Neither has any knowledge of other individual agents, social constructs, or social structures. Is autonomy a fruitful concept in considering such simple individual agents? We, therefore, confine our attention to intentional agents, and note the positive correlation of usefulness of the concept of autonomy with social abilities of the individual agent.

An intentional agent can exhibit various degrees of autonomy as determined by how much influence local and non-local there is in its decision making process. Local limitations on autonomy include constraints on intentional and physical abilities, while non-local limitations can be exerted through social values, e.g., avoid damage to the concerns of other individual agents, norms, e.g. keep to the right, legal restrictions, e.g., do not exceed the objectives, and the need to cooperate. An advocate of a more sophisticated position with respect to individual agent autonomy might claim that autonomy is a social notion, and as such, can only be a property of individual agents endowed with social properties interacting with other such individual agents in a social situation. Within this camp, there can be many variations with one of the simplest being that expressed in [7]. It can assert that the forms of social autonomy could be defined in terms of different forms of social independence, and that each component of the architecture or necessary condition for a successful action could define a dimension or parameter of autonomy, since it can define the resources necessary for the goal to achieve. The question of what individual agent characteristics are required for an agent to be considered social. Could an individual agent be intentional to be social? This implies that the existence of a dependent social relation in an environment is enough to establish the autonomy. This is required for the user, the agent or the system? Could an individual agent be intentional, selfish, goal driven? Could an individual agent be capable of introspection, self-awareness and self-evaluation to be considered social?

This approach implies that dependency and autonomy are inverses of each other, but it is possible that an individual agent could be dependent on another agent and yet still remain fully autonomous, if the agent has the capability of ending the dependency relation at will. This suggests a distinction between different levels of autonomy. An individual agent who is dependent on another agent, but who retains control over that relation has given up first order autonomy, but retained some level of autonomy. Dependencies likewise can be more complex and subsumed. When an individual agent depends on input from other individual agent to establish its own dependency relations, then this agent has an interaction dependency on the second.

A stronger position on autonomy requires that an individual agent not only be social, but also be capable of reliably assessing its own capabilities. The claim is that an individual agent is not fully autonomous unless it has justification for believing that it is autonomous. Capability must be part of autonomy in the sense that an individual agent is autonomous with respect to a particular task or action only if that agent has the ability to complete the task or action. The greater the individual agent's warranted belief in its own capability the greater the agent's autonomy with respect to the relevant tasks.

In some environments, individual agent intentions and decisions are highly constrained by the environment. For example, an agent (a physical one, or robot) driving on a blocked path has fewer options than an agent driving on a free way. These constraints limit the agent's autonomy in the sense that a trusted and self-aware agent will reconsider activities that have a sufficiently high probability of resulting in negative or undesirable consequences. On the other hand, if the environment is safe for the agent, then choices are unconstrained, and autonomy is expanded. This example illustrates a common sense idea about the relationship between autonomy and the extent of an individual agent's choice, namely, the larger the number of choices that an individual agent has available the greater the agent's autonomy. While it is certainly the case that an agent with no choice has no autonomy, the converse does not hold. Consider an individual agent presented with a choice between an action that will cause its maximum objectives to be completed and an action that will affect the user's petitions. How much autonomy does such an individual agent have? Autonomy evaluation must consider quality of choices as well as number of choices. Indeed, having too many choices can be detrimental, if the individual agent does not have the resources to properly evaluate those choices.

6. Individual agent variations

Individual agents vary in their autonomy. These variations are due, in part, to differences in behavior, negotiation style, or individuality [6]. In the case of agents, we can take individuality to be a collection of persistent patterns of behavior such as trust and cooperation. The agent community has begun developing individual agents with synthetic personality [8], mentioning laziness, helpfulness, dominance, and conflict checking as agent personality traits [9]. Obviously, individual traits contribute to the individual agent's capability of autonomy. For a rough understanding of individual variations of autonomy we suggest two dimensions or axes. The first dimension is a *dominance/rigidity/flexibility* scale. *Dominance* constrains agent interactions by demanding: (i) certainty, (ii) independence, (iii) norms and values, (iv) boundary precision, and (v) control. Highly dominant individual agents demand precision and are less flexible. One aspect of this kind of rigidity is the need for certainty of effects of actions (by self and others) and certainty of information available to them. With higher certainty, dominant individual agents are more confident in their actions and rely on their choices.

When there is a lot of on uncertainty, an individual agent may not feel in control of its environment and may feel less confident about its decisions. Another aspect is the need for independence, and/or the avoidance of dependence. A highly dependent personality requires the assistance of others. A dependent agent may require constant direction and reinforcement.

In the opposite extreme, an independent individual agent will avoid assistance from others, and be fiercely dominant, which can affect its ability to be part of a team. Another aspect of rigidity is pointless adherence to rules, orders, laws, conventions, norms, and values. A rigid individual agent will be unyielding in following rules. On the other hand, an individual may seek to avoid rules and regulations. The formal aspect of rigidity is boundary maintenance. Individual agents differ in their tolerance of limits, sharing norms and cooperation, and some tolerate flexible values while others demand precise boundaries and limits. A more complex aspect of rigidity is the need for control and dominance. This is related to the need for a particular level of independence. Some individual agents have higher need to be in control while others are capable of reaching goals with less control. This could be expressed with a German expression: *Auftragstaktik*. In this case the user (a human or another agent) gives their subordinate agents a clearly defined goal (a mission or objective to achieve) and the tools, information or elements needed to accomplish that goal with a time within which the goal must be reached. The subordinate agents then implement the order independently. The subordinate agent is given, to a large extent, the planning *initiative* and a freedom in execution which allows flexibility in execution. It is more of a method of leadership: a much different grade of autonomy in a complex environment with distributed control. Then, direct orders should be an exception in this case, while tasks (or missions) should be the standard instrument of achieving complex objectives. But clearly the relationship between rigidity and independence is in need of further investigation.

A second axe or dimension is a scale representing *submission/capacity/perception* which is the individual agent's capabilities to objectively perceive an agent's attributes that constrain interaction, which will be measured on submission as a *competence attribute*. Individual agents that do not accurately perceive uncertainties can believe that they are in deterministic environments and may conceive of their autonomy being circumscribed. Those that perceive more uncertainties are better able to form a more complex sense of autonomy. Individual agents, who see they to be highly dependent, will sense relatively lower levels of autonomy as opposed to those who are oblivious to these dependencies. Sensing the extent to which an individual agent's decisions are guided by trust, norms, and values can give an individual agent a sense of security or/and lack of freedom. The ability to perceive control is another aspect of an individual agent's capacity. Sensing higher levels of control is generally reassuring for an individual agent and will lead to a sense of freedom and experience of higher autonomy.

The exact relationship between distributed control and autonomy appears to be very complex. At one end of the capacities dimension are individual agents with the highest capacities and in the other end there are individual agents with the lowest capacities.

7. Environmental variations

Whereas freedom is implied from autonomy, freedom to act or decide does not imply autonomy. Freedom is the social component of autonomy. Autonomy is also more than this external sense of freedom. An individual agent must satisfy internal conditions, beyond socially extended autonomy, in order to be autonomous. Autonomy can interpreted as a combination of socially warranted freedoms to behave and internally perceived capabilities to decide. When individual agents are in groups, organizations, and institutions, their individual agent autonomy is altered by the properties of the group. This effect may be caused by their membership, their representation of group to others, or their participation in collective behavior. In settings where social obligations are rigid and matter a great deal, autonomy tends to be how an individual agent relates to those social rules. In contrast, there are many environments where few or no constraints or strict rules and norms of conduct to frame agent behavior. In such environments, individual agents are free to be 'wild', non social or unaffiliated.

Individual agents, as members of groups, are subject to the social climate within which they are embedded. Their memberships and allegiances constrain their decision making and provide them with a set of behaviors, rights, duties, and obligations governed by a set of norms and values. This may augment or detract from their individual agent autonomies. Autonomies are affected by the individual agent's degree of commitment and loyalty to the groups to which they belong. As we explored above in our consideration of individual agent variation, individual agents do vary in their tendency toward commitment and loyalty. However, here we are suggesting that the existence of groups to which an individual agent may belong produces a set of attributes for an agent's autonomy deliberation.

We point to a need to develop reasoning methods for autonomy that account for an agent's membership in groups. Given that an individual agent is a member of a particular group, then it represents the group in its interaction with non-group members, the individual agent assumes the group's goals and autonomy and augments it to its own. A representative must embody the essential components of the group it is representing and use it in reasoning about the group's autonomy.

In collective action or collective decision-making, the group as a whole owns the action or decision. An individual agent's autonomy toward the collective action or decision can only be conceived of as a contribution. This can be in terms of voting or vetoing power in the case of decision-making. In the case of physical or social action, an agent's autonomy is represented by the extent to which the individual agent facilitates the group's intent.

8. Limits of autonomy

Agents that interact with humans must be designed with particular attention to human safety and to not endanger human goals as well. Problems can arise when agents are fully autonomous and their actions are un-interruptible. Conversely, problems can also arise when an agent pays too much attention to human input when the human has insufficient knowledge of how the agent operates. Both agents that are excessively passive and agents that are excessively active can be harmful. Humans in the loop of agents need to be able to adjust the activity level of agents dynamically, that is, the autonomy level of agents needs to be adjustable. This seems to suggest a multi-tiered approach to agent autonomy. Agents may operate with certain nominal autonomies under normal circumstances but under heightened safety or concern conditions, agents should be switched to other modes when authorized human users manipulate their autonomy. Changing agent roles in interaction has been reported in mixed initiative work [10]. Another promising area is empowering agents to reason about shared norms and values [11]. Since accounting for all contingencies is not realistic, agents need to have the ability to reason for themselves about whether their human supervisor would approve of their choices and assumed autonomies.

An agent's assumed level of autonomy may have unintended effects on other agents in a multi-agent setting. When tasks among agents are coupled, cooperating agents need to use a shared notion of autonomy to take into account one another's actions. Sharing autonomy is useful for harmonizing agent autonomies in order to account for one another's influence and to avoid negative influences [12]. Collective autonomy requires mutual trust among agents. Groups of agents may develop a notion of autonomy that belongs to the entire group. Individual agents will conceive of autonomy of their group. However, the group's autonomy can only be altered by collective actions such as negotiation. There can be problems when an individual agent in such a group misunderstands the group's autonomy when it represents the group. This can cause harm to the group or others.

9. Autonomy in a complex world

To date autonomy still is a poorly understood property of computational systems, both in theoretical and practical terms, and among all properties usually associated with multi-agent system (MAS) it is this property being most controversially discussed. On the one hand, it is argued that there is a broad range of applications in complex domains such as e-commerce, ubiquitous computing, and supply chain management which can hardly be realized without taking autonomy as a key ingredient, and that it is first of all agent autonomy which enables the decisive features of agent-oriented software, namely robustness, flexibility and the emergence of novel solutions of problems at run time. On the other hand, it is argued seemingly convincingly that autonomy mainly is a source of undesirable and chaotic system behavior. Obviously, without a clarification of these two positions, it is unlikely that MAS (having autonomy as a real property and not just as a catchy label) become broadly accepted in real-world, industrial and commercial applications.

Artificial intelligence paradigms today are moving towards a more distributed agent-based architecture. It is argued that when intelligence is approached in such an incremental manner, the reliance on global representations and reasoning disappears [13], [14], and [15]. Specifically, the agents are physical or computational entities that are (i) situated in an environment, (ii) posses resources of their own, (iii) can perceive the environment, (iv) have practically no representation of their environment, and, (v) execute behaviors which may offer useful services. Autonomous agents are not directed by commands from a user. Instead, they are directed by a set of likelihoods to behave in a particular way. Autonomous agency became popular with the work of Brooks [13], [14], challenged the deliberative paradigm in AI (the classical planning paradigm that was also slow due to brute force search) by building stimulus-response based entities on this subsumed architecture.

10. From Wolf to Poodle

Now, we address the problem of building and monitoring a long-living digital ecosystem inhabited by autonomous agents; the agent has a large number of relatively complex and varying tasks to perform [16]. Biology suggests some ideas about the way animals deal with a variety of tasks: brains are made of specialized and complementary areas/modules; skills are spread over modules. On the one hand, distributing functions and representations has immediate advantages: parallel processing implies reaction speed-up; a relative independence between modules gives more robustness. Both properties might clearly increase the agent's efficiency. On the other hand, the fact of distributing a system raises a fundamental issue: how does the organization process of the modules happen during the life-time? And in both cases are relaying on the autonomy of the agents system.

Agents are individual entities with true autonomy or mere 'domesticated' ones? They are obedient and dependent or autonomous and free? Domestication is the process of hereditary reorganization of wild animals and plants into domestic and cultivated forms according to the interests of people. In its strictest sense it refers to the initial stage of human mastery of wild animals and plants. The fundamental distinction of domesticated animals and plants from their wild ancestors is that they are created by human labour to meet specific requirements or whims and are adapted to the conditions of continuous care and solicitude people maintain for them.

Domestication has played an enormous part in the development of mankind and its material culture. It has resulted in the appearance of agriculture as a special form of animal and plant production. It is precisely those animals and plants that became objects of agricultural activity that have undergone the greatest changes when compared with their wild ancestors. After wild dogs learned not to bite the hand that fed them, French poodles weren't far behind. Some argue that humans adopted wolf pups and that natural selection favoured those less aggressive and better at begging for food. Others say dogs domesticated themselves by adapting to a new niche—human rubbish dumps. Scavenger canids that were less likely to escape by running away, especially because of danger or fear, from people survived in this niche, and succeeding generations became increasingly tame. All that was selected for was that one trait—the ability to eat in proximity to people. At the molecular level not much changed at all: The DNA makeup of wolves and dogs is almost identical. The dog evolved in the company of humans and cannot exist without them. Even the vast majority living "wild" as village scavengers depends on proximity to humans. Further, domestication is a rare event requiring special skill, but the dog is a domesticated wolf. Evolutionary biologists are looking at dog DNA for evidence that even a toy poodle is a wolf in dog's clothing [17]. Domestication is a phenomenon whereby a wild biological organism is habituated to survive in the company of human beings. Domesticated animals, plants, and other organisms are those whose collective behavior, life cycle, or physiology has been altered as a result of their breeding and living conditions being under human control for multiple generations.

In a related way the notion of domestication is used in domestication theory that describes the process of the 'taming' or appropriation of technology by its users. Animal species must meet some criteria in order to be considered for domestication: (i) Pleasant disposition, (ii) Temperament disposition to obey, (iii) Modifiable social hierarchy — Social creatures that recognize a hierarchy of dominance can be raised to recognize a human as its pack leader. A herding instinct arguably aids in domesticating animals: tame one and others will follow, regardless of chiefdom. To deal with the increasing complexity of large-scale computer systems, computers must learn to manage themselves, in accordance with high-level guidance from humans and a vision that has been referred to as autonomic computing. Here one sets out to adopt a bio-inspired vision to develop "wild" agents able to fulfill the exigencies of the total autonomy, in order to obtain from them a type of "domesticated" agents which make the tasks that are entrusted to him. In a few words, your French poodle will obey your order about your sofa, with a wolf you must fight. The bio-inspired lesson is that if we build a complex agent system we should decide between a wild, really autonomous entity (a "running with wolves" agent) or a more domesticated one (like a toy poodle acting on behalf of the users), but highly dependent entity (on users, programmers and maintenance).

11. Cognition, Robots and Autonomy

Research in robotics has traditionally emphasized low-level sensing and control tasks including sensory processing, path planning, and manipulator design and control. In contrast, research in cognitive robotics is concerned with endowing robots and software agents with higher level cognitive functions that enable them to reason, act and perceive in changing, incompletely known, and unpredictable environments. Such robots must, for example, be able to reason about goals, actions, when to perceive and what to look for, the cognitive states of other agents, time, resources, collaborative task execution, etc. In short, cognitive robotics is concerned with integrating reasoning, perception, and action within a uniform theoretical and implementation framework (using methods drawn from logic, probability and decision theory, reinforcement learning, game theory, etc.).

The use of robots and software agents is becoming more and more widespread, with many commercial products on the market. Complex applications and the need for effective interaction with humans are increasing demand for robots that are capable of deliberation and other high-level cognitive functions. Models from cognitive science and techniques from machine learning are being used to enable robots to extend their knowledge and skills. Combining results from mainstream robotics and computer vision with those from knowledge representation and reasoning, machine learning, and cognitive science has and will continue to be central to research in cognitive robotics. The current scene in cognitive science is characterized by a growing interest in the ecological-embodied-enactive approach [18], and [19]. According to this view cognition is best characterized as belonging to embodied, situated agents. In this approach we consider possible implications of the enactive approach for future agent (and robotic) ecosystems. In particular, the enactive approach in perception would lead to agents and robots whose ability to perceive not only depends on, but is constituted by, their possession of certain sensor motor skills [20]. Noë argues that perception and perceptual consciousness depend on capacities for action and thought, that perception is a kind of thoughtful activity. We propose to consider the question to what extent an embodied and situated individual agent (or robot) should and could develop its own subjective point of view.

12. Background and roots

Since the mid-1980's, there has been rapidly growing interest in research studying the behavioral and evolutionary foundations of cognition and intelligence. Studies of computation as an emergent phenomenon, cognition as adaptive behavior, coordinated perception and action, and evolutionary learning techniques (such as genetic algorithms) can all be broadly classified as work in Artificial Life. The study of systems which exhibit adaptive behavior has received growing attention from workers in fields as diverse as ethology, robotics, neuroscience, cognitive science, economics and linguistics.

Increasing numbers of Artificial Intelligence researchers are addressing such fundamental issues, as an adjunct to the more usual focus on high-level cognitive functions such as natural-language understanding or planning for complex tasks.

Work in this area is often holistic: complete autonomous agents are studied as cognitive systems interacting with their environments. This places emphasis on understanding mechanisms responsible for generation of behavior, rather than on individual agent cognitive functions; and hence on understanding the interactions between the agent and its environment, rather than on isolated disembodied intellects. The term autonomous agents include animals, mobile robots, and software agents inhabiting virtual realities. Artificial autonomous agents are more commonly known as animats.

Methods of study, and mechanisms developed, vary depending on the phenomena addressed: rule-based systems, neural networks and simple finite-state automata have all been employed with success. We are interested in understanding cognition in ethological, ecological, and evolutionary contexts. Some of our studies involve building autonomous mobile robots, while others take place in complex computer simulations that provide virtual realities for simulated agents. Some of our work also addresses wider issues in complex adaptive systems, examples include: emergent computation, bio-inspired agent systems, theoretical and philosophical issues and the global dynamics of complex digital ecosystems.

13. Enaction in agent systems

The current scene in computer science is characterized by a growing interest in the ecological-embodied-enactive approach [21]-[25]. According to this view agent cognition is best characterized as belonging to embodied, situated agents. In the digital ecosystem would be possible implications of this complex approach for future digital systems. In particular, the enactive approach in perception would lead to agents whose ability to perceive not only depends on, but is constituted by, their possession of certain sensor skills [23]–[25]. In the future will be necessary to consider the question to what extent an autonomous (embodied and situated, also) agent could develop its own subjective point of view, and how the users will cope with that trait.

Classical definitions fell prey to the problem, as Jerry Fodor [28]-[30] put it, that no one has ever managed to come up with any knock-down definitions. Perhaps the biggest error with classical approach was the focus on static definitions. If we treat concepts as dynamic entities, constantly (if often only incrementally) in flux as an agent interacts with her environment and the other members of her society (population, community), might there be some more mix? Rather than being a priori representations, concepts might be seen as continually enacted: synchronized patterns of association between the mental world of an agent and the organization of her environment, dependent both on how the agent is situated and embodied. In discussing these enactive definitions, the goal need not be a complete account of concepts but only one important component in such an account: an account that may also leave room for an updated version of imagism, that other longstanding tradition in theories of concepts.

The term *enaction* was proposed by Francisco Varela, see [19], in order to designate a new paradigm in cognitive science, based not on the metaphor of the computer as in classical cognitivism, but instead on the metaphor of living organisms. The aim is to contribute to the maturation of this new paradigm and to the formation of an identifiable application in digital ecosystems and agent community.

Any paradigm in cognitive science must meet two main requirements: the theoretical core must provide a principled answer to the enigma of the relation between matter and mind; and the paradigm must provide for trans-disciplinary articulation, notably between the domains of philosophy, psychology, linguistics, neurosciences and Artificial Intelligence. The initial proposals of Maturana and Varela [31], [32], where Cognition = Life = Autopoiesis, should be critically explored, in order to identify their limitations with a view to overcoming them. In particular, it will be crucial to avoid the trap of a restriction to low-level sensori-motor cognition, by ensuring the passage to high-level cognition such as language, consciousness and culture.

Finally, it will be important to clarify the relation between the paradigm of enaction, and other related approaches: in particular phenomenology; the philosophy of life and individuation [33], [34]; constructivism [35]-[38]; psychology; the ecological approach [39]; autonomous robotics, etc. being this list neither extensive nor exclusive.

Enactive interactions are inspired by a fundamental concept of interaction that has not been exploited by other approaches to the design of human-computer interface technologies. Mainly, interfaces have been designed to present information via symbols, or icons. In the symbolic approach, information is stored as words, mathematical symbols or other symbolic systems, while in the iconic approach information is stored in the form of visual images, such as diagrams and illustrations. Enactive knowledge is neither symbolic nor iconic. It is direct, in the sense that it is natural and intuitive, based on experience and the perceptual consequences of motor acts. Enactive knowledge is information gained through perception-action interactions with the environment. Examples include information gained by grasping an object, by hefting a stone, or by walking around an obstacle that occludes our view. It is gained through intuitive movements, of which we often are not aware. Enactive knowledge is inherently multimodal, because motor actions alter the stimulation of multiple perceptual systems. Enactive knowledge is essential in tasks such as driving a car, dancing, playing a musical instrument, modeling objects from clay, performing sports, and so on.

Enaction is a term coined in psychology [40] and used in a particular biological approach [19], according to which cognition is fundamentally a feature of living organisms in a dynamic adaptive relationship with their environment. Only recently the term has gained widespread currency in domains such as human-computer interaction. In the same kind of view, the physicist Jean Petitot [41] proposes the idea of a Phenophysics, based on the theory of Morphogenesis of the mathematician R. Thom [42], according to which the necessary condition for categorization to occur, is the presence of specific singularities in the dynamics of physical sensorial events, on which categorization can get a grip. These theories are used in signal processing, shape recognition and can be used in extraction of emotive patterns in signals. Other related concepts are presently developed also in relationship with artificial intelligence and robotics. The proper domain is that of the so-called embodied cognition, which gives much importance to action and perception in the definition and simulation of intelligent behaviors, by focusing the attention on parallel, distributed architectures, on adaptive behavior of different kinds (not only high order symbolic capacities) and on the possibilities offered by the dynamic systems modeling of behavior.

14. Final remarks

The focus during the developing of an Open Negotiation Environment should be on the autonomy of the agents pursuing their goals in the Digital Ecosystem, using bio-inspired computing, agent-based modelling and social networks based intelligence [43]. This bio-inspired approach is applied in combination with service orientated architectures to support business ecosystems. Current negotiation platforms, such as Business-to-Business electronic marketplaces and Internet trading platforms are centrally managed and not yet fully trusted or too expensive for SME's. The solution in a negotiation environment should be affordable, open, not centrally controlled, and supporting the sharing of knowledge via flexible security and trust policies. The agents would be able to learn and evolve with the changing conditions in an open-source solution ensuring transparency and sustainability. By using the highly autonomous agents in a complex environment all players (users, clients and others agents) will benefit from reduction of dependence to behave and transactional costs.

We have argued that autonomy is not uniformly conceptualized, and that an account of autonomy must also account for variations between individual agents and environments. This variability (between individual agents, populations, communities, ecosystems) is a key factor to the affect autonomy, and is determined strictly by agent interactions and dependencies. This work proposes to select and design complex features for agents that must match the requirements of their environment for autonomous behavior.

Our approach emphasize, from the start-point of fundamental DE's [43], the study of how reciprocal agent fluxes across utterly different environment and digital ecosystems can affect the structure and dynamics of local agent interactions and emphasize the need to account for the resulting indirect interaction between them. These approach emphasize the need to think across ecosystems when studying community dynamics and managing agent populations with complex cycles. These DEs are created primarily to investigate aspects of biological and other complex systems [44]-[46], rather than to provide a service for human users. Newly applications and developments are placing DE's in the mainstream of everyday life, from business to leisure.

A further body of theory treats ecosystems as complex adaptive systems [47]. These models provide a theoretical basis for the occurrence of self-organization in both digital and real ecosystems. Self-organization results when interactions among agents and their environment giving rise to complex nonlinear behavior. It is this property that provides the underlying potential for scalable problem-solving in a digital environment.

By comparing and contrasting theoretical ecology with the anticipated requirements of digital ecosystems, we have examined how ecological features may emerge in some systems designed for adaptive problem solving. Specifically, we suggested that a digital ecosystem, like a real ecosystem, will usually consist of self-organized agents that interact both with one another and with an environment. Agent population dynamics and evolution, spatial and network interactions, and complex dynamic fitness landscapes will all influence the behavior of these systems. Many of these properties can be understood via well-known ecological models [48], and [49].

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