Approaches to Embed Bio-inspired Computational Algorithms in Educational and Serious Games

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Abstract

Bio-inspired computational algorithms can be effectively employed to develop games for learning. In the present paper we will introduce different approaches to embed this kind of models in Serious and Educational Games. According to a multi-level description of game design process, bio-inspired computational algorithms can be visible to the user, residing at an external, shell level; can be invisible to the user, residing at the core, internal level; can be employed in the evaluation and tutoring level pertaining to user profiling and supporting learning and teaching processes. This different approaches are explained by introducing some educational games example: BreedBot in which bio-inspired computational algorithms are used to develop the player-game interaction and are explicitly visible by the user; Learn2lead, where these techniques are used to model the game mechanics and are invisible to the user; and Infanzia Digi.tales project in which these techniques are functional to develop smart educational materials by implementing adaptive tutoring systems.

1 Introduction

In recent years an epochal turn has been observed in education coming from a twofold pathway. On one side, a growing effort has been devoted to the use of new technologies, in particular ICT technologies, as educational tools. Technology-Enhanced learning (TEL) has intercepted this tendency by promoting new educational practices, new communities and new ways of communication [Balacheff et al., 2009]. On the other side, a lot of interest has arisen about the use of game for learning. This interest is witnessed by the numerous research branches that emerged, game-based learning [Tobias and Fletcher, 2011], edutainment [Charsky, 2010], gamification of learning [Kapp, 2012], just to cite some. In particular many games have been developed under the label Educational Games and Serious games which include card, board and videogames. Serious Games (SG) are games that educate, train, and inform [Michael and Chen, 2005], sharing the same educational mission.

Why games are so appealing as educational tools? Games are often models of reality that simplify what happens in real world including some relevant aspects of it. They are micro-worlds [Rieber, 1996] that can work as a lab where to experiment something: behaviours, emotions, strategies in a somewhat protected environment. Games can also start from reality and go beyond, this is the case for hyper-realistic games as war simulators or surrealist games.

For this paper purpose, we will now focus on digital/electronic games that, in the last years, have assumed an important role in the game market with an ever-increasing diffusion. Also their application in education has been massive for many reasons. Digital entertainment games have some specific features that are very useful in an educational context: games engender motivation [Malone, 1981], are engaging [Gee, 2003] and exploit learning by doing [Aldrich, 2005].

To fully exploit game potentials, design plays a crucial role [Chandrasekaran, 1990], as it must consider the interaction between the player and the digital game, in the more general frame of human-computer interaction [Lieto and Radicioni, 2016]., keeping the lessons derived from neurosciences, cognitive science and psychology, related to attention, executive functions and spatial cognition [Bhatt and Freksa, 2010].

To implement these aspects, computational models can be taken into account, in particular bio-inspired computational models can be effectively embedded in games.

Bio-inspired computational models, at the edge between natural and artificial, are extremely fit for educational goals [Ponticorvo et al., 2016] if the goal is to teach biological, psychological and social matters, as it will be evident later, because they allow to convey knowledge about dynamic and complex system, emergence, evolution and development.

2 Serious Games design process

The SG design process can run according to a multi-level framework, with two concentric levels, the shell and core level and a ubiquitous one, the evaluation and tutoring level [Dell'Aquila et al., 2016], represented in Fig.1. The shell and the core level are present in every game of game, and, more in general in almost every cultural product. The shell level represents the visible content that is immediately accessible to players. It frames the game engine, the game dynamics that are hold in the core level. The third level, the evaluation and tutoring level, is characterizing for

Educational and Serious games, as it allows, on the teachers side, to understand if and how the player/learner has acquired the concepts conveyed by the Educational game.

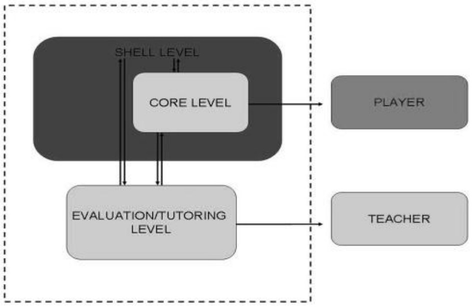

Figure 1 A multi-level game design process with shell, core and evaluation/tutoring level. Shell and core levels can be found in every kind of game whereas the evaluation/tutoring level characterizes educational games

2.1 The shell (game narrative) and core (game mechanics) levels

The shell level represents what the player sees, what we call the game narrative. Digital games, as many other cultural products, are expressed trough a narrative metaphor that carries out the crucial role to give sense to the game. Let us consider for example, the Monopoly game. Throwing the dice and moving on the boxes has the meaning to represent real estate commerce and this strongly helps to engage the player.

In designing the shell level we have to define the context: who are the agents, what actions they can display, what interactions are possible between them. The shell level, based on narrative, holds an hidden level with a specific operation, the game engine, the core level.

The game engine allows to implement core functionalities related to game dynamics, for example related to physics, animation, artificial intelligence, etc. The core level defines precisely the characters with sensory-motor endowment, the environment with its features and every possible interaction between characters and characters/environment.

These levels are in dynamic interaction and have strong effects one on the other: the narrative provides a frame where the hidden content resides.

The shell level is necessary in providing a semantic context to educational activities whereas the core level defines the skills or the abilities to be transferred.

In digital games, the core can host the game engine based on computational algorithms.

2.2 What the core level holds

The core level holds the game mechanics, the engine. It can be conceptualized differently depending on the kind of digital game we aim at building.

In the case of educational games, the core modeling process is addressed not only by the chosen kind of game, but also on what content we want to convey.

If our goal is to build educational tools and materials which are related to biology, psychology and sociology, exploiting concepts such as emergence, complex and dynamic systems, evolution and development, we can glean from a wide class of bio-inspired algorithms.

Bio-inspired computing [Pintea, 2014] is a field of study that exploits the study of natural phenomena to apply it to machine learning: from evolution to genetic algorithms [Goldberg, 2006], from natural complex systems to cellular automata [Chopard and Droz, 1998], from the nervous systems to artificial neural networks [Patterson, 1998].

A particular class of bio-inspired algorithms, Agent Based models (ABM), is, in our opinion, particularly well-suited for game design. ABM [Helbing, 2012] is a class of computational models used to simulate phenomena belonging to various domains ranging from biology to psychology and sociology starting from the action and interaction of simple agents. These agents are autonomous and can represent individual or collective entities such as groups. We adopt a wide definition of ABM: in SG, ABM is not used to understand collective behaviors starting from simple rules, but it aims at representing in detail agents interaction and the agent itself. In other words, a great effort is devoted to modelling agents too, in this respect resembling multi-agents systems approach [Van der Hoek and Wooldridge, 2008] where agents can be very complex.

If we adopt ABM, in the core level, every agent is defined in function of its sensory features, what it sees, hears, smells, touches in the setting and about the core, and action endowment, what it can do to affect the core state. These actions must follow game rules that are defined both by setting constraints and by agent actions chances residing in the core level.

As we are in the domain of digital SG, agents can also be artificial agents: in this case the agent is not human, but a bot whose artificial intelligence can rely on bio-computational models as well.

2.3. The evaluation and tutoring level

In a SG, a relevant role is played by the evaluation and tutoring level. A SG has an explicit educational goal that is to allow the player to accomplish specified educational objectives. The evaluation and tutoring layer complements the core and shell layers. This level analyze player’s game performances relatively to the specified training objectives, and provides the players and the trainer, whose role is indeed relevant in Educational and Serious games, with important information and data about the learning process. At this level we find learning analytics [Siemens, and Baker, 2012], which are the measurement, collection, analysis and reporting of data about learners to improve the whole learning process. This level is also crucial from the teachers’ point of view, as it provides specific tools and function to support teaching processes.

3 Bio-inspired computational models in the proposed multi-level framework

Bio-inspired computational algorithms can enter the SG design process in many different ways and at different level thus producing a diversified game typology. If the designer's goal is to build a SG that is explicitly addressed to biology-related matters, bio-inspired computational models can flow from the core level to the shell level, thus becoming visible to the user. On the contrary, the designer can leave a traditional appearance to the game whereas the bio-inspired computational models work in an invisible manner, staying in the core level. Moreover bio-inspired computational models can be employed on the evaluation/tutoring level, providing the artificial evaluator with a guise of artificial intelligence thus supporting the teachers' role. In the following sections we will present some example of such usage of bio-inspired computational models.

3.1 Bio-inspired computational models in the shell level: when game narrative and mechanics converge

The first case is the use of bio-computational algorithms starting from the core and arriving to the shell level: the game mechanics are directly visible to the user. The shell becomes transparent and what happens in the core level can be accessed by the player; this way the SG becomes a virtual laboratory where the user can directly manipulate the relevant variables involved in the game, thus determining the game evolution in an immediate manner. This direct manipulation takes place in a protected environment where failures or error do not determine a menacing outcome. This virtue is counterbalanced by the unavoidable complexity reduction.
These games use Bio-inspired computational models for an explicit interaction mechanism. The user interacts with the game using traditional bio-inspired computational methods, for example by evolving a population, training an organism, setting up an ecological system, etc.
An interesting example of this kind of games is Breedbot and its sequels Bestbot, and Brainfarm [Miglino et al., 2008; Ponticorvo et al., 2006].
These are integrated software/hardware platforms that allow players, even without any particular computer skill, to breed, within customizable virtual worlds, artificial organisms that can be downloaded onto real robots (Fig. 2).
These games can be reached though the following links:

BestBot http://eutopia.unina.it/bestbot

BrainFarm http://150.146.65.191/BrainFarm

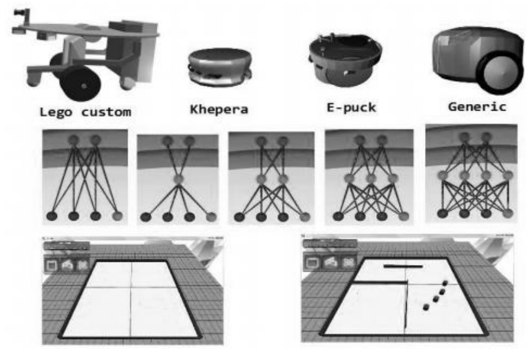

Figure 1 The Brainfarm interface with custom neural networks

The breeding is implemented through a user-guided genetic algorithm. The software side of Breedbot shows users a population of nine wheeled robots, with infrared sensors and motors and controlled by a simple feedforward neural network, representing an artificial nervous system. The neural network parameters are encoded in a genetic string that will undergo an evolutionary process guided by either the users (artificial selection) or the machine (automatic selection). In this latter case the player can anyway manipulate the relevant evolutionary variables.
By manipulating directly the parameters related to the genetic algorithm the player can understand the underpinning dynamics and experience different evolutionary pathways in a controlled environment.
In this example various bio-inspired computational models that flow from the core to the shell level in a pervasive manner. First of all, the robots are conceived as agents in the wide conception of ABM. Each robot, in fact, is seen as an embodied agent interacting with a physical environment and with other robotic agents.
Their artificial intelligence is implement adopting a connectionist framework with artificial neural networks and their evolution/development carries out adopting evolutionary algorithms. Moreover the player can affect directly the evolutionary pathway acting as a breeder that selects the preferred agents. The breeder acts as an expert using knowledge and expertise to select the best solutions.

3.2 Bio-inspired computational models in the core level: using bio-inspired algorithms to model the game engine.

The second case is the use of bio-inspired computational models in the core level. The game engine is invisible for the player that interacts with the game in a traditional fashion, without perceiving what happens in the game engine. Bio-inspired computational algorithm are used to model complex system but the user does not interact with the computational models directly.

These models can be derived from scientific theories in many different domains and, obviously, the choice is driven by the designer educational objective.
As hinted in the introduction, one model that can be fit for game design is ABM. This kind of models can be employed to model both the interactions between agents and the agent itself. Moreover, if a careful description of agent is provided in terms of what it perceives, it knows about the external environment, and how it makes decisions upon its action, it is possible to model the agent behaviours according to a specific psychological theory.
Agent based modelling has been used to build Serious Games in various contexts: for crowd simulation, economics and artificial societies, just to cite some.
An interesting SG that exploits ABM to model and teach team dynamics is LearnToLead (L2L) [Di Ferdinando et al., 2015]. L2L is a web-based game where the player covers the leader role and learns theories about leadership by governing a team of artificial agents, the followers. The theoretical starting point is the Full-Range Leadership Theory (FRL), a well-known and widely-employed theory that explains leadership dynamics in small groups [Bass and Avolio, 1994]. The game mechanics is developed by using two bio-inspired computational algorithms, namely ABM and artificial neural networks.
In L2L game the shell level, the game narrative is clearly separated from the core level: it appears as a point and click game in a 2D environment which is played on the web. It takes place in a firms office, as it is evident from some decorative elements: desks, chairs, PCs and mobiles, stacks of paper, etc. (Figure 3).

Figure 3 L2L office where the game takes place

This physical setting varies across all game levels looking nicer and nicer as the player advances in career.
In L2L there is hierarchical interaction between the player acting as a leader and the followers, artificial agents. The human player must manage the team of artificial agents, which stands for a team of workers in a bank, a post-office branch or a local government office, for example.
The game is played across numerous levels in which the player will lead teams in different corporation departments, from the catering department to the research and development one.
The game reproduces the day-by-day running of the department, including jobs with precise deadlines and workloads. The player must assigning staff to work on those jobs. The basic challenge is to ensure that followers finish all jobs in time and the leader must manage the assignment of followers on jobs and their performance. With a smart management, the team can complete a respectable number of job tasks within their deadlines. However, leadership involves more than management, and if the player uses a strategy for developing followers, there will be an effective advantage in the game, in terms of completed tasks.
Indeed the followers are not all equals, as they are well-characterized by ability level, motivation level, stress level and personalit. The player, acting as a leader must take these variables into account in assigning players to jobs and making action to affect the cited variables. It is, for example, possible to run workshops, organize team-building events, perform one-to-one coaching, send memos, propose training course, give lectures about performance, deliver evocative speeches at staff meetings, etc.
On the core level, L2L is a logical structure where an asynchronous interaction happen between the leader and the followers. A turn-based structure to play is implemented, so that players always have an unlimited amount of time to carefully consider their actions, and consult reference material about FRL if necessary before making an action. The player acts on the work environment and team dynamics by setting the working plan of each follower and influencing followers motivation, stress and their contribution to the team, with the action recalled before.
More specifically, when the leader takes some decisions about one or more followers, these decisions affect the followers. These decisions become input for the follower's network and these inputs from the leader, together with the ones coming from the external environment, modify the agents' internal states that, in turn, will change and influence the follower contribution to team job (Fig. 4).
In brief, each agents' behaviour is determined by external and internal variables: the first ones consist of leader's behaviour (interact with followers), the working environment (total amount of workload, approaching of deadlines), and the social interaction with other followers.
The internal ones are instead those relative to the psychological aspects of followers, between which motivation is the most important. In particular, three sub-components of motivation are simulated: intrinsic, reward and fear. The intrinsic component represents the internal form of motivation, driven by an interest or enjoyment in the activity. On the opposite, the reward and fear components model external forms of motivation, which rely on external pressures like desire for reward, or fear for punishment. The peculiar features of these three

components have been modelled using a different temporal decay. In particular, the intrinsic component has a slower decay than reward and fear, but can be activated only by appropriate leader behaviours (typically related to leadership style).
Another important variable to consider is the followers' personality, which has been modelled taking into account the McClelland [1978] theory. In particular, three different personalities (or motivational drivers, according to McClelland theory) were considered:
a. *Achievement*: followers pursue excellence in performance, a continuing drive for doing better all the times. Excellence can be achieved through individual efforts;
b. *Affiliation*: followers are interested in establishing, keeping, and restoring close personal relationships with others;
c. *Power*: followers pursue a status with impact on others. High power motivation induces highly competitive behaviour.
The stress level must be kept under control during the game as well, because it affects the effort and the contribution of followers to the team work.
Moreover, the followers ability has been simulated, as there are followers smarter (faster) than others doing their jobs. Thus, followers' performance is linked to their ability.
All these variables interact among each other, with the external stimuli and with the leader's behaviour, as depicted in Figure 4.
Personality and ability try to capture what the FRL theory says about individual consideration, so that the same leader action may have a different impact on followers with different personalities or abilities. On the other side, the leader who aims at raising the team motivation as high as possible needs to perform some individualised considerations. Leaders should also pay attention when assigning followers to the same workgroup, as conflicts may emerge depending on followers' personality (Fig. 4).
In this example, Bio-inspired computational models are used to model the core of the game using an ABM approach, moreover each agent artificial intelligence is modelled using an artificial neural network, whose input and output represent the already described external and internal variables.

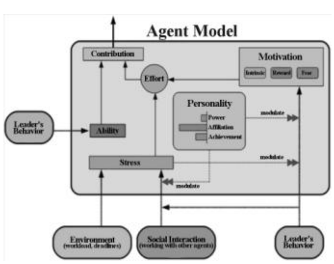

Figure 4. Agent model in L2L

In this game, the bio-inspired models are completely invisible to the users. In fact, they serve as effective technique to implement the FRLT, whereas in Breedbot (see previous section), the bio-inspired models are relevant for the interactive process.
This kind of games allows to observe dynamics that can emerge form agents interaction and this is an important positive feature. It permits, in fact, to experience directly, even if in a controlled situation and a safe environment what happens in a group context, thus complementing more traditional and theoretical learning methods.
The negative point is represented by the possibility that the emerging complex dynamics can slip away and generate unforeseeble outcomes.

3.3 Bio-inspired computational models in the evaluation and tutoring level: when Bio-inspired algorithms model human trainer expertise

The last case is about bio-inspired computational model in the evaluation/tutoring level. This level, that is characterizing for educational games, foresees a smart interaction with the user/player. This smartness resides in adapting, inferring, profiling and anticipation, functions that mimic human teachers' actions.
In other words, at this level, it is necessary to foresee tools that extract two kinds of information: on one side, data about the learner such as learning style, preferences, weakness and strengths and, on the other side, about teachers behaviour in order to reproduce artificially human trainer expertise.
The evaluation/tutoring level implements what an human expert in education would do while representing in an effective and concise way what the learner does.
For example, this level provides an appropriate and timely feedback to player action, it adapts to player special needs according to actual performance and the desired educational goals, it tracks player performance in terms of achievements and improvements. This smart interaction can mediated by the use of Intelligent Tutoring Systems (ITS) [Carbonell, 1970].
Many examples can be found about this issue, as it has arisen a strong interest since research about ITS was born in the seventies (for a recent review, see Wenger [2014]).
One key feature in ITSs is the presence of a student model.
To address the educational process it is crucial to pay attention to a particular student's cognitive and affective states in order to tailor the whole teaching and learning process on the individual.
To achieve this goal, it is necessary to build a student profile and a fruitful way to do it is to employ specific data analysis methodologies.
Learning analytics rely on huge amount of data that can be used to improve learning. Educational data mining, for example, is a research branch devoted to processes designed

for the analysis of data from educational settings to better understand learners and the settings which they learn in.
Data mining, for specific learning goals too, can be run adopting bio-inspired methods as neural networks [Lu et al., 1996].
It can be also useful to run data clustering analysis and Bio-inspired methods can be used for clustering data, thus illustrating another way these methods can be embedded in the evaluation/tutoring level.
Data clustering consists in finding homogeneous groups in a dataset and Bio-inspired algorithms can be employed to find new methods for clustering that include the human expert role. In particular Interactive Evolutionary Computation (IEC) techniques [Bintrup et al., 2006] can be used. In this case, a human breeder selects cluster configurations on the basis of their graphical visualizations.
Data clustering is based on the analysis of explicit information and quantitative variables (dimensions) that describe a given phenomenon and on latent and implicit information captured by human cognitive mechanisms: this implicit analysis is what characterize human experts, also in education domain. The human experts are usually trained for many years to recognize (categorize) natural phenomena on both explicit and latent information even if they cannot explain how they do it.
IEC allow to embed this feature in Evolutionary computation with the intervention of a human operator that interacts with the artificial evolution process.

The positive feature of this kind of models is that, applied to teaching and learning processes, they can capture interesting regularities that help profiling the student/player/user. This process supports teaching and improves learning, but it doesn't foresee a complete teachers substitution. This compensates the dark side these methods display, that is the temptation to image the educational process with a learner totally immersed in a digital, automatic, artificial environment without any human contact.
It is our opinion, on the contrary, that, especially in some life periods, such as infancy, the social dimension of education cannot be neglected: it should be rather supported by these methods and algorithms that try to replicate teacher/student interaction but not cancelled. This is the rationale behind Infanzia Digi.tales, an on-going research project whose goal is to provide smart digital objects to be used in learning and teaching process in children.
Moreover it is worth underlining that this example is doubly interesting as it shows how to build learners profile using bio-inspired computational models and indicating a new way of implementing a smart interaction.
Introducing an human expert in the evolutionary process, it shows how to go beyond ITS and propose a new framework with educational agents (EA), working in dynamic interaction. If we conceive both learners and teachers as agents, ABM allows us to model effectively this interaction and to try to build bio-inspired artificial experts in education as well as bio-inspired artificial learners. This can be done starting from the regularities extracted by Educational data mining and by modeling learner/teacher and their interaction exploiting, once again bio-inspired computational algorithms.

4. Discussion

The design process that leads to Educational and Serious Games can derive useful hints and borrow models from bio-inspired models, meaning that artificial intelligence has a deep impact on how cognitive elements are embedded in people-centred design for games [Vanden Abeele and Van Rompaey, 2006].
The multi-level framework proposed in this paper goes in this direction and allow to explicitate relevant issue on the future direction for the contribution of artificial intelligence and cognitive issue to game design. Indeed bio-inspired computational methods can be applied effectively in designing Serious and Educational games as they are isomorphic to teaching subject in the case of biology, psychology, sociology.
Moreover teaching and learning with digital games can lead to neglect some relevant aspect that are, on the contrary, fundamental in other educational contexts, such as physical embodiment, autonomy, social interaction, evolution and development. These aspects allow biological organisms to successfully adapt to unknown and changing environments and widen artificial intelligence to embodied artificial intelligence [Pfeifer and Iida, 2004].

Acknowledgments

The INF@NZIA DIGI.tales has been funded by Italian Ministry for Education, University and Research under PON-Smart Cities for Social Inclusion programme.

Authors would like to thank Onofrio Gigliotta for Breedbot materials.

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