# Multi-Agents Based Virtual Environments for Cultural Heritage

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***Abstract*— This paper focuses on the integration of artificial intelligence methods in multi-agent virtual environments for cultural heritage applications and especially virtual museums and exhibitions. Multi-agent systems are considered here as being autonomous social organizations capable of developing dynamic personalized virtual environments. In this respect, some of the most common artificial intelligence methods in intelligent virtual environments are discussed. Three different sub-domains of intelligent virtual environments are identified and presented, aiming at an enhanced virtual reality experience. The paper concludes by highlighting the importance of artificial intelligence applications in cultural heritage, and the dynamics of the virtual museums with personalized content, based on the profile of the user and the need of the case.**

***Keywords—realistic virtual environments; intelligent virtual agents; multi-agent systems; cultural applications; virtual reality***

## I. INTRODUCTION

In recent years, there is a growing trend for the development of serious games in diverse fields including entertainment, cultural heritage, education, artificial intelligence, sociology, military and health systems [1, 2]. Serious games are highlighted as innovative and important tools for the development of applications broadly accepted by all ages (children, adults and seniors) [3]. Serious games have been widely adopted in cultural heritage, for applications such as virtual exhibitions and museums and have been the subject of applied research and development for several years [4, 5]; nevertheless, there are still challenges for further research targeting the enhanced interactive realistic simulations of ancient worlds or cultural sites and exhibitions. In a sense, serious games can be considered as an efficient approach for blending domain specific activities, like those in cultural heritage and education, with gaming.

Gamification [6] is the result of applying game mechanics into diverse domains, in order to engage users and enhance their knowledge and performance. The importance of playing has been emphasized in many studies from various domains. According to Brown & Vaughan [7], playing is an archetypical activity that arises from primordial biological structures existing even before the conscience or the capacity for speech; as Brown & Vaughan emphatically stated, playing is not something a person decides to do. According to Nicholson [8], gamification is nothing more than the use of specific game design approaches and techniques in various environments, in order to attract people in problem solving and to enhance their contribution.

The application of Agent and Multi-Agent Systems (AAMAS) in cultural heritage is gaining increasing attention, and especially in supporting new technological solutions for museums, art exhibitions, archaeological sites, historical event simulations and more [9, 10]. Attempts to merge intelligent agent approaches with virtual reality and artificial worlds have given birth to the field of intelligent virtual environments. Aylett et al. [11] call the merging of artificial intelligence with a virtual environment an *Intelligent Virtual Environment* (IVE) if it concerns the virtual world itself, or an *Intelligent Virtual Reality System* (IVRS) if it concerns the system that creates and renders the world. Thus, an IVE is a virtual environment resembling the real world inhabited by autonomous intelligent entities exhibiting a variety of behaviors. These entities may be simple static or dynamic (like a revolving sun, or traffic lights), virtual representations of life forms (virtual animals and humans), avatars of real-world users entering the system, and others. In fact, the structure and content of a virtual environment are only restricted by the nature of the target application and the designer's imagination and, of course, the available computing resources. On the other hand, an IVRS is a back-end system that automatically develops the content of the virtual environment.

Artificial intelligence that is based on multi-agent systems and is applied to serious games, is generally useful for modeling non-player characters (NPC) behavior and for playing the game as an NPC just for the experience of play (not to win). Whether the purpose for the game is educational, recreational, or simulation, NPC agents need to act *believably* and *motivated*, in order to empower learning or boost the engagement level of the game. The usual approach followed is the construction of top-down (ad-hoc designed) agent architectures that represent various cognitive, social, emotive and behavioral abilities. The focus has traditionally been on the modeling of the agents' behavior, but also on its appropriate expression under particular contexts. A popular way of constructing a computational model of agent behavior is to base it on a theoretical cognitive model such as the Ortony-Clore-Collins (OCC) model [12], which, in its application in computer science, represents an attempt to emulate human-like decision making and mechanisms of appraisal and coping, depending on a set of perceived stimuli (other agents, events and objects in the environment).

This paper focuses on intelligent personalized virtual environments for cultural heritage applications. Of special interest is to derive a framework of rules, theory and best practices for the development of the virtual environment by autonomous agents and multi-agent systems. By combining knowledge from games research and artificial intelligence, three sub-domains are identified that may interact to automatically create an interactive personalized virtual environment.

## II. The Playground Of Multi-Agent Systems

The term *agent* is widely known and used, but there are several different definitions. In general, it refers to an entity that makes its own choices about how to act in its environment without any influence from a leader or a global plan. All agents have three key components: *perception, reasoning, and action*. These three components operate within the context of some environment, as shown graphically in the left part of Fig. 1. In this respect, there is a dynamic bidirectional relationship of an agent with its environment, affecting the environment and its perception by the agent.

The framework described in this section defines a specific structure for the environment: how it is affected by the agent's actions, how it affects the agent's percepts, and whether other agents are involved. With general but careful assumptions about the environment, agents can effectively reason about appropriate actions to select.

Agents who learn (*learning agents*) are a particular type of agents. In systems with learning agents the details of the environment are initially unknown. The agents receive information about the environment through their interactions, by selecting actions and observing their effects through their perceptual inputs. In learning agents there is an additional input signal, the *reward*. This reward depends on the environment and the agents' actions. The reasoning applied by the agents relies on a learning process that repeatedly interacts with the environment with the goal of maximizing the rewards it receives over time.

In general, multi-agent systems can be best visualized along a primary axis, the *socialization quality*, which spans the *cooperation through competition* spectrum, and a secondary axis, which spans the size spectrum of the studied agent societies [13] (see Fig. 2). Cooperation can be established when agents cooperate for a common goal, sharing utility functions and knowledge [14]. For example, industrial robotic systems cooperate to create production lines, just like RoboCup teams cooperate to win a match. By using the typology of conventional sociology, three levels of organization are identified and studied in multi-agent systems [13]:

- *The micro-social level*, where interest focuses on the agent and the interactions among two or several agents.
- *The level of groups*, where interest shifts to groups, and where agent groups work towards a common goal, and the group may also work against other groups.
- *The level of global societies* (*populations*), where interest shifts further to the dynamics of a large number of agents, along with the general structure of the system and its evolution.

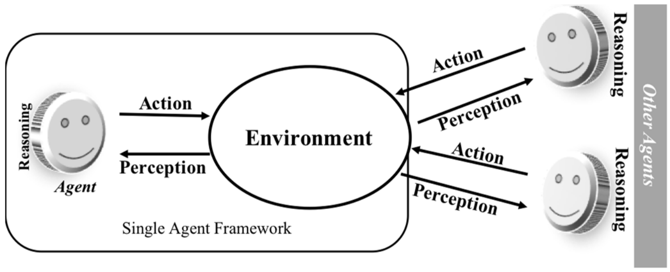


Fig. 1. Multi-agent framework: multiple agents all distinguished from their environment and composed of perception, reasoning, and action

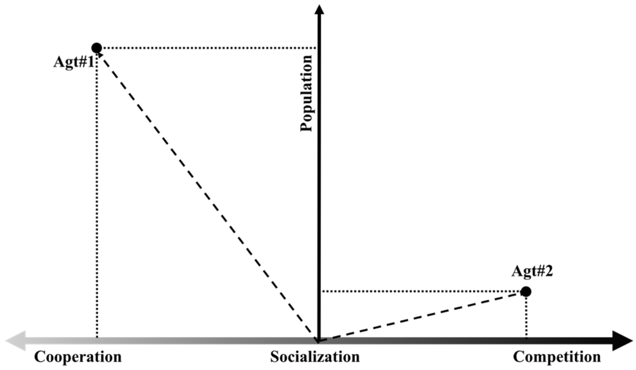


Fig. 2. Typical categorization of the study of agents in multi-agent systems

In general, societies demonstrate a mixture of qualities, so the full spectrum from the individual to small groups to the overall population is of interest, especially when learning is also involved [15, 16, 17, 18]. As an example, *Agt#1* in Fig. 2 is a highly cooperative agent studied in a large society, whereas *Agt#2* is a highly competitive agent studied within a small group of agents.

## III. Artificial Intelligence Methods In Multi-Agent Systems

Though learning is a principal hallmark of intelligence, the wider agents' community has converged on a set of conditions which can lead to an agent being characterized as acting intelligently [19], namely (if the agent):

- acts appropriately for the circumstances and its goals, given its perceptual and computational limitations,
- is flexible to adapt to changing environments and goals,
- gains experience and has learning capabilities.

An agent, typically, cannot observe the state of the world directly; moreover, it only has a finite memory and it does not have unlimited time to act. To alleviate these constraints, researchers have usually employed one of some signature artificial intelligence methods for agents, which operate in multi-agent virtual environments:

- *Tree search* [19]: refers to methods which search the space of future actions and build trees of possible action sequences, using algorithms such as Minimax, and Monte Carlo Tree Search.

- *Evolutionary computation* [20]: refers to population-based global stochastic optimization algorithms such as genetic algorithms, simulated annealing.
- *Ad-hoc authoring*: refers to methods employing static ad-hoc approaches without any form of search or learning such as finite state machines [21], behavior trees [22], utility-based AI [23].
- *Supervised learning* [24]: refers to learning a model that maps instances of datasets to target values, such as classes, using artificial neural networks, support vector machines, decision tree learning, etc.
- *Unsupervised learning* [25]: refers to algorithms that find patterns in datasets where no predefined target values exist, using clustering methods such as *k*-means, hierarchical clustering and self-organizing maps.
- *Reinforcement learning* [26]: refers to methods that solve problems, where a sequence of actions is associated with positive or negative rewards, but not with a "target value" (a correct action); typically, these temporal difference algorithms or of the dynamic programming family etc.

Al methods are incorporated in intelligent multi-agent systems, in which the intelligent part of the agents is covered by the aforementioned AI methods.

## IV. Enhanced Virtual Environment

This section introduces three core sub-domains for developing enhanced virtual reality user experiences in cultural heritage with AI methods applied through agent and multi agent systems. Researchers in the domain of virtual environments focus on two sub-domains, including dynamical *knowledge modeling*, management and presentation and dynamical *content generation*. On the other hand researchers in the domain of AI in games, focus on three distinct sub-domains, including *player modeling*, *content generation* and *gameplay* [27], with *content generation* being a common sub-domain for both research areas. Fusing those aspects may result in three different sub-domains: dynamic content generation, knowledge modeling and gameplay. This is depicted in Fig.3 that presents some key attributes for each sub-domain.

*Dynamical Content Generation* [28, 27] refers to generating content for the virtual environment, autonomously or with limited human involvement. The goal of the dynamical content generation methods is to remove the need for humans to generate content in large scale personalized virtual environments. In serious games, dynamical content generation is used to maximize the learning effects of a game, or perhaps the addictiveness of a "casual" game by focusing on educational purposes. Terrains, characters, artifacts, exhibits, story elements, game rules, textures, music, multimedia etc. are the main objects that can be generated dynamically. There are basically two methods for dynamical content generation, offline and online, the first of which focuses on content generation during the development of the game, whereas the second focuses on the real-time content generation.

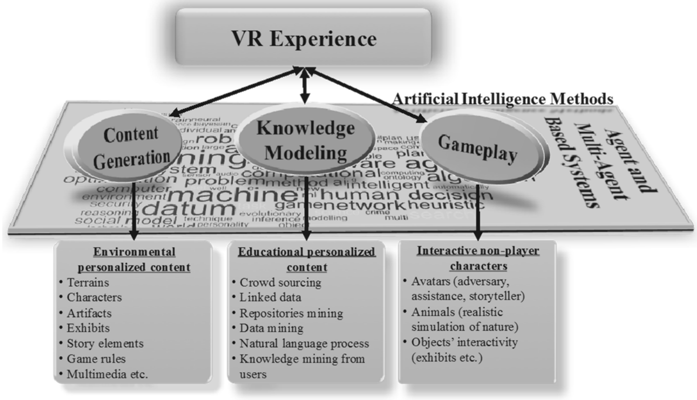


Fig. 3. The structure of an enhanced virtual reality experience

*Knowledge Modeling* is the process of creating a computer interpretable model of knowledge or standard specifications about a kind of process and/or about a kind of facility or product. Knowledge is a combination of information and experience, context, interpretation and reflection [29]. Knowledge Modeling was established several years ago as a research field, and started with traditional information systems and databases, to distributed systems, and the Web [30]. Today knowledge modeling aims to exploit the distributed data on the Web. Today a well-known source of knowledge modeling is *crowd-sourcing*, which is of special interest for cultural heritage applications like virtual museums. For example, *Europeana* is a digital platform for cultural heritage, with content based on *linked open data* technologies, which are offered through an application programming interface (API). Several studies have already shown the importance of crowd-sourcing and knowledge modeling in cultural heritage [31, 32, 33].

The *Gameplay* sub-domain, in many, probably most, virtual environments includes methods and tools for various non-player characters (NPCs). These characters are controlled by agent controlling algorithms. The requirements of these algorithms have led to an emphasis on behavior authoring methods such as finite state machines and behavioral trees, as AI methods based on search, optimization and learning have not shown advantages in playing to gain experience. A common disadvantage has been a perceived lack of predictability and control with such methods. Some of the most known AI methods used in playing games include tree search-based approaches [34], reinforcement learning [26] and supervised learning [24]. The integration of NPCs in virtual environments focuses on enhancing the user experience in dynamic environments with realistic, non-boring content and concepts. AI in serious games is generally useful for modeling NPC behavior and playing the game not for winning, but rather for the experience of play.

Nowadays virtual museums focus on personalized content for achieving a most effective user experience, which is why the term *Personal Virtual Museums* (PVM) has been coined [35]; the underlying technologies are based on the three sub-domains presented in Fig. 4. Some of the key features of PVMs are:

- PVMs are dynamical systems supporting interpersonal communication as well as knowledge modeling and management

- PVMs explore a pan-institutional, modular system of learning objects for the creation of new authored content
- PVMs exploit a structured, external linking system (linked data technologies) to provide a richer context for item level content
- PVMs provide "rich content"—rich multimedia that maximizes the use of images, video, audio and computational media as much as possible, along with comprehensive context for individual items
- PVMs provide dynamical educational personalized content to users based on their requirements

The application of these key factors in PVMs, by using artificial intelligence methods, focuses on the development of dynamic, pleasant, user-friendly, attractive, personalized educational virtual worlds for various uses, such as education, work simulation, etc.

## V. INTELLIGENT VIRTUAL ENVIRONMENTS IN CULTURAL HERITAGE

Today, there are some important ingredients involved in realistic simulations based on intelligent agents, which are still the subject of debate over their origin, formal background, definitions, methods, applications and future directions [36]. For social simulations to be meaningful, it is necessary to implement realistic models for both the virtual agents, the environment and their interactions; the latter has long been the subject of multi-agent systems and reinforcement learning [37]. A lot of attention has been given to the definition of accurate models for agents (e.g. behavioral, decision-making and interaction models) [38, 39, 40, 41]. The approach of building intelligent virtual environments, in which the virtual environment is artificially being developed and created, sometimes in real time, based on the progress and the profile of the users is relatively new [38].

In addition, the realistic simulation of virtual crowds [42] has diverse applications in architectural design, emergency evacuation planning, urban planning, personnel training, education, virtual museums and entertainment. There are several approaches that aim to create better representations of crowds in virtual environments, with the agent-based methods being the most successful; agent-based methods focus more on individual behavior, whereas crowd simulations aim to exhibit emergent phenomena of groups. Not surprisingly, combinations of these approaches can deliver results of substantially enhanced realism and, often, the crowd that is being simulated by agent-based models is designed as a multi-agent system, in order to develop different behaviors that may cooperate or compete each other. This approach increases the realism of the simulated crowds by highlighting the social attitude of artificial intelligence agents.

A technical challenge in AI simulations is the path planning [43]. There are several algorithms that improve the navigation of agents in virtual environments, resulting in more realistic and detailed simulations [43]. An example is shown in Fig. 5, where the highlighted ground is the 'walkable' area for the agent that plans its route taking into account any objects that might act as obstacles. The dashed line shows the shortest path to reach the user, assuming this was the agent's goal.

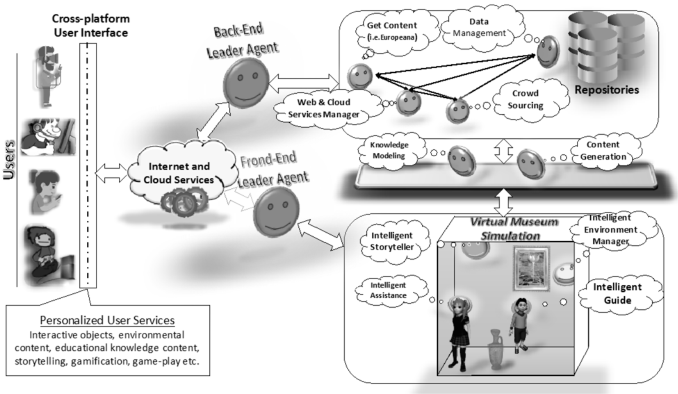


Fig. 4. Ideal multi-agent based dynamical personal virtual environment.

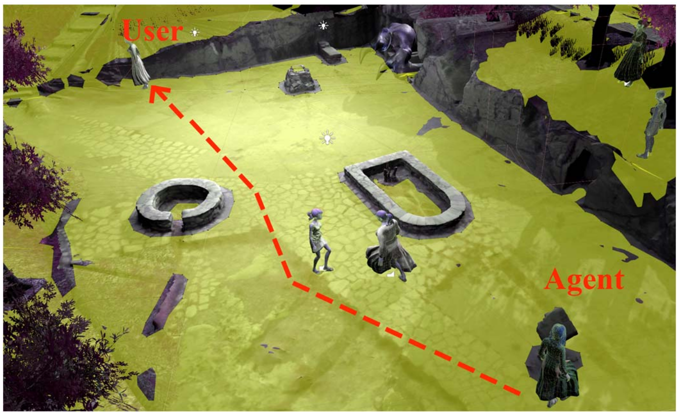


Fig. 5. Navigation area for an AI agent with a specific goal.


Fig. 6. AI agent-based virtual guided tour.

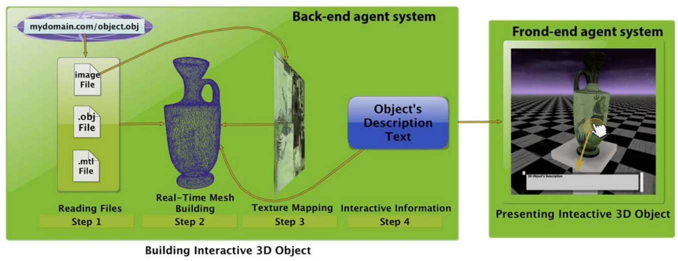


Fig. 7. Multi-agent based content generation and presentation

Another important contribution of AI that enhances the user experience in virtual environments with cultural and educational topics (like the virtual museums) is the use of virtual agents for guided tours [44]. A virtual agent leads to an intelligent conversation with users, responds to their questions and performs adequate nonverbal behavior. Further enhancements may include virtual agents-guides that discuss with users and present the space [45], and adaptive, personalized exhibition spaces. An example of this concept is shown in Fig. 6, where an AI avatar asks a user (also represented by an avatar in the virtual world) to explore together the environment, unfold a story and provide information about specific points of interest.

The use of AI for the understanding of player experience can drive and enhance the design process of games. Game designers usually explore and test a palette of mechanics and game dynamics that yield experience patterns they desire to put the player through. Player states such as engagement, fear and stress, frustration, anticipation, and challenge, define critical aspects of the design of player experience, which is dependent on the genre, the narrative and the objectives of the game. As a result, the player experience can be improved and tailored to each individual player but also augmented via richer experience-based interaction.

Nowadays several 3D objects are distributed over the Web, with rich metadata accompanying and describing them. Fig. 7 depicts an example where a back-end AI agent searches the Web and retrieves 3D objects and their metadata attributes based on the users' profile. The back-end agent builds the object dynamically. The right side of Fig. 7 depicts a front-end agent, which presents the 3D object to the users based on the linked open metadata for the object.

## VI. A Brief Discussion

Designing for museum personalization is a challenging task. Museum visitors are unique personalities with specific goals and preferences. Any profile initialization method has to take into account multiple user factors to be truly effective and usable in a museum context. It needs also to be based on an appealing and non-intrusive design, and to be brief and interesting. This section serves as a *kick-off discussion* on a generalized efficient and effective *framework for the development of the next generation virtual worlds with personalized content in cultural heritage applications*, following the analysis in the previous sections:

- We aimed at summarizing some of the most important key factors relating to PVMs that focus on dynamical environments composed of external (linked open) resources based on user profiles. Education, training and entertainment seem to be achieved by PVMs.

- We aimed at highlighting the importance of crowd-sourcing, AI and the AAMAS technologies towards more engaging and robust virtual environments. AI is being applied in the area extensively, but due to the immaturity of the field, there is still plenty of room for more AI applications.

- We aimed at proposing the use of three core sub-domains (content generation, knowledge modeling and gameplay) that can serve as the general framework for developing enhanced virtual environments based on multi-agent systems and gamification, by merging the research interests of two relevant domains, (virtual museums and game AI). The envisioned systems have the potential to provide more accurate and targeted educational content on cultural heritage applications.

- In the margin of the proposed general framework, we aimed at presenting a novel approach for the quantitative classification of an agent's *socialization quality;* this is influenced by the general distinction in the behavior of agents according to their cooperation and competition behavior in AAMASs.

A general such framework for the development of virtual museums with personalized content based on AAMASs is shown in Fig. 8. In this framework, the AAMAS is a central component that creates the virtual world and the content for the user by exploiting a constant exchange of information among the user (profile), the museum aims (educational, scientific, etc.) and the resources, in real time.

## VII. Conclusions

Apparently, the combination of ideas and technologies from virtual environments and intelligent AAMASs is a very active field, with many different research groups concerned with different aspects [10]. This paper summarizes some of the key factors relating to PVMs that focus on a dynamic environment composed by external resources providing content based on user profiles. Education, training and entertainment seem to be achieved by PVMs. In addition, this paper highlights the importance of crowdsourcing, AI and the AAMAS technologies towards greater and more robust virtual environment, and presents a preliminary generalized framework for the binding of AAMASs, virtual environments, personalized access and cultural heritage.

## VIII. Acknowledgment

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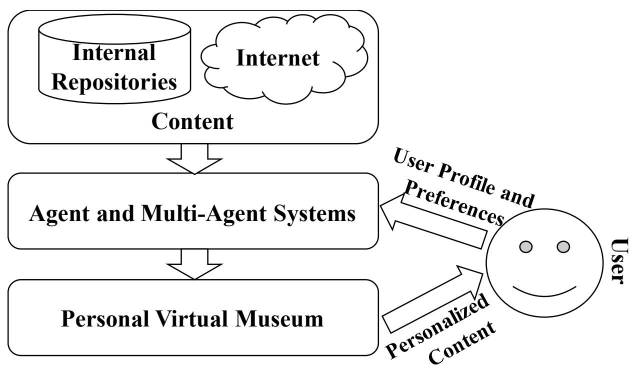


Fig. 8. AAMAS-based framework for cultural heritage virtual worlds.

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