Automatic Extraction of Gameplay Design Expertise: An Approach Based on Semantic Annotation

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Abstract. A Game Based Learning System (GBLS) constitutes an interesting learning environment. However, many problems are facing the general adoption of learning approaches based on this system. For instance, complexity of GBLS design process and problems of integrating learning outcomes with fun aspects constitute the major challenges. Therefore, novice game designer have not only to acquire specific skills and expertise but also to acquire them in an efficient and active pedagogical manner. For that aim, extraction and representation of knowledge related to GBLSs design become necessary to render possible accessibility and transfer of that knowledge to novice actors and further to meet aforementioned challenges. In this context the use of learning ontology techniques based on semantic annotation of gameplay description seems promising as it facilitates knowledge extraction, elicitation process, and grants more formal knowledge representation which allows answering to growing needs of sharing data within and across organizations and actors.

Keywords: GBLS · Gameplay · Automatic knowledge extraction · Ontology learning

1 Introduction

Despite the numerous Internet monitoring tools and content management systems to acquire Experts' knowledge, Knowledge collecting process is still performed manually. Generally, this gathering process leads to the construction of knowledge sheets that sum up all the information (theoretical and technical competencies), which make difficult the knowledge accessibility, representation and sharing.

To tackle this issue, several research studies have shown the importance of integrating various tools to enhance knowledge discovery and extraction [1].

C. Vaz de Carvalho et al. (Eds.): SGAMES 2016, LNICST 176, pp. 53–63, 2017.
DOI: 10.1007/978-3-319-51055-2_8

In this paper, we aim to extract GBLS gameplay design knowledge and make them accessible to novice GBLS designer. For that purpose, we use automatic knowledge extraction based on semantic annotation. This allows to: (i) Exploit the considerable increase of freely available data about gameplay design, (ii) Acquire and present knowledge in a machine-readable and machine-interpretable format, (iii) Answer to the growing need of making this knowledge accessible and (iv) to foster opportunities of sharing data within and across organizations and actors participating in GBLSs design processes.

This proposal follows the following steps: problem identification and motivation, definition of the objectives for a solution, design and development, demonstration and validation.

This paper is organized as follows: In Sect. 2 we describe the problem's statement and major difficulties to overcome; in Sect. 3 we present works related to expertise and knowledge extraction approaches, automatic knowledge extraction methods as well as works having dealt with eventual tentative of extracting GBLS gameplay design knowledge; in Sect. 4 we detail the approach of Automatic Extraction of GBLS Gameplay Design Expertise by presenting fundamental steps of extraction process. In Sect. 5 we conclude and outline our future works.

2 Problem Statement

GBLSs are considered as a branch of serious games that deal with applications that have defined learning outcomes [2].

Actors participating in this process still suffer from many challenges that span all over the design and development cycle. Problems of integrating enough educational outcomes without sacrificing the fun characteristics and problems inherent to the complexity of each step in a GBLS design process are already well entrenched and critical which require relevant expertise to be resolved.

According to [3], designing serious games where fun qualities and serious aspects are integrated and respected requires specific skills and expertise in terms of theoretical and technical knowledge background.

Unfortunately, novice game designers who do not have technical and theoretical competency inspired from both educational and video games systems cannot successfully create GBLS.

For that aim, we shall have an appropriate environment allowing the participating actor to curry out his/her tasks efficiently either alone or collaboratively. The overall system should be enough flexible and able to cope with business domain changes or IT changes. The same system must provide to novice actors relevant assistance accordingly to their skills, tasks and context in order to achieve their jobs effectively. Figure 1 presents fundamental components of our future system which is based on two major components. The first one is relative to gameplay design process; it presents steps to follow by the game designer [4]. The second one contains four models (gameplay model, game designer model, error model and pedagogical model). The gameplay model presents the set of knowledge to be required, actions to be performed and rules to be respected by the game designer. The game designer model presents skills and context of the current actor which can determine the type of system intervention. The error model, presents the set of game designer errors, which are classified in categories. The Pedagogical model determines the teaching methods as well as the way in which the intervention can take place (alert notification, assistance messages, a detailed explanation …..).

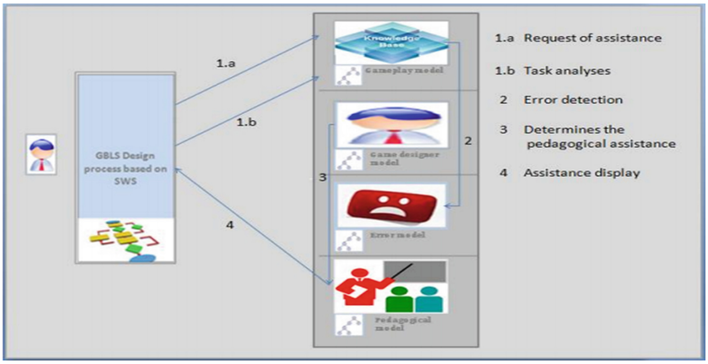

Fig. 1. Architecture of the GBLS design platform

In this paper we focus on the development of the gameplay model through the extraction and representation of knowledge related to GBLSs design and especially that of gameplay design.

3 Related Work

Over the last decade, due to the considerable increase of freely available data, the extraction of relevant information from structured and unstructured content has encouraged researchers in acquiring expertise knowledge.

In this section, we will present expertise knowledge extraction approaches as well as automatic knowledge extraction methods. Alternatively, we will describe eventual attempts among knowledge extraction applied to GBLS design and we attempt to highlight their respective limitations.

3.1 Knowledge Acquisition Methods

According to [5], there are five methods that can be used to extract expertise knowledge from human experts. These are respectively method of familiar tasks, method of structured and unstructured interviews, method of constrained processing task and method of tough cases. These methods require a detailed analysis of expert's tasks, tactics and strategies.

The shortcomings of these methods are that they:

- Provide imperfect results if they are applied separately.
- Provide data in non standardized format which requires further analyses and transcription.
- Are based on a single expert which can result a single line of reasoning that makes it difficult to evoke in depth discussions of the domain. Moreover, not all expert knowledge resides with the single expert. And therefore, these methods might not actually be very informative about the expert's reasoning.

3.2 Automatic Knowledge Extraction Methods

To overcome limits of methods cited in Sect. 3.1, automatic knowledge extraction seems very promising since it allows to:

- Exploit the considerable increase of freely available data.
- Discover relevant information from structured and unstructured sources.
- Acquire knowledge in a machine-readable and machine-interpretable format.

In this context, the use of learning ontology techniques can facilitate not only knowledge extraction and elicitation processes, but also grants more formal knowledge representation which allows to answer to the growing need of sharing data within and across organizations and actors.

Learning Ontology, also called ontology population and enrichment, is the task of extending an existing ontology with additional objects as instances, concepts and semantic relations. This task is considered as a knowledge acquisition task [6]. The process of constructing, enriching and populating ontologies is considered as resource demanding and time-consuming. Thus, the automated or semi-automated construction, enrichment and population of ontologies are highly desired.

In [7] authors propose an incremental process to populate ontology, including 4 steps:

- Ontology-based Semantic Annotation: The instances of the domain ontology are used to semantically annotate a domain-specific corpus in an automatic way. In this step disambiguation techniques are used exploiting knowledge captured in the domain ontology.
- Knowledge Discovery: An information extraction module is used in this step to locate new ontological instances. The module is trained, using machine learning methods, on the annotated corpus of the previous step.
- Knowledge Refinement: A compression-based clustering algorithm is used in this step for identifying lexicographic variants for each instance supporting the ontology enrichment.
- Validation and Insertion: A domain expert validates the candidate instances that have been added to the ontology.

This process demands human intervention to validate and insert extracted entities, which constitutes a very time consuming and error prone task.

In [8], authors decompose the ontology learning process into six steps. Starting by identifying terms (objects), then defining synonyms terms, thereafter selecting concepts and finally establishing relations and acquiring rules.

This process neglects an important task related to redundancy detection, which constitutes the major defect of this approach.

Authors in [6] consider that the ontology learning process involves population, enrichment, and inconsistency resolution steps. Indeed, an initial ontology is used to analyze and extract information from a corpus. The extracted information is used to populate and enrich the ontology. This process continues until no more information can be extracted from the corpus. In every cycle the consistency of the ontology is checked and redundancy problems are detected.

3.3 Knowledge Extraction Methods Applied to GBLS Design

Authors in [3] present an overall classification system for Serious Games. The intention of this classification is to guide people through the vast field of Serious Games by providing them with a general overview. For that aim, authors present a G/P/S model (Gameplay/Purpose/Scope model) that propose a classification based on gameplay, purpose and scope criteria of the game.

Authors have built a collaborative online database. This database assembles the classification information about 550 Serious Games. The G/P/S model it is not able to provide detailed information concerning serious games design knowledge which constitutes its main limitation.

In similar approaches, [9–11] propose classification systems to index games according to the "markets" that use them (i.e. the kind of people who play them).

Proposed solutions are not able to provide detailed information concerning Serious Games. It can only differentiate between games according to a limit number of criteria (target audience, purpose, …). These limits restrict the general use of this system to respond to GBLS designer's requirements. Additionally, they are based on the applications of Serious Games rather than on the games Design process.

To conclude, we did not find any research work that aims to extract automatically GBLSs design knowledge, and present that knowledge through a precise and semantic model. At the best of our knowledge, there are no works based on semantic web technologies to automatically extract information specific to GBLS from texts and to give a structured organization to such knowledge.

In order to reap the full benefits of automatic knowledge extraction techniques, we opt to use learning ontology techniques.

In the present paper, we will focus on the enrichment and the population of the GBLS gameplay ontology developed in [12] to:

- Entail the semantic description of the concepts related to GBLS gameplay design process.
- Present the set of experts' knowledge about gameplay design.
- Specify the knowledge about tasks to be performed when designing GBLS.
- Present the set of knowledge that the novice game designers have to acquire.

4 Automatic Extraction of GBLS Gameplay Design Expertise

4.1 GBLS Gameplay Design Expertise

Helping beginners to acquire a new set of competencies related to GBLS gameplay design consists on acquiring a set of fundamental competencies responded on both, the game designer profile and the game design job. Figure 2 presents GBLS game designer competencies model.

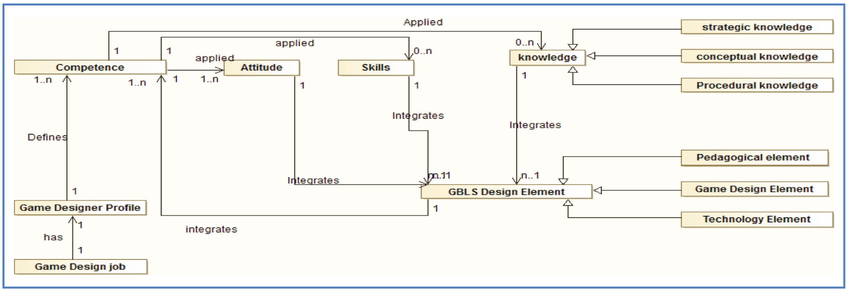

Fig. 2. GBLS designer competencies

These competencies are applied on three axes:

The first axe includes attitudes: which present the work methods, they determine not only the sequence of steps to follow but also capability of adapting their approach to the project problems, the communication and coordination with the GBLS design team. The second axe concerns skills related to manipulating new technologies as the GBLS design constitutes a permanent evolution field. The final axe concerns Knowledge that includes three main types [13] as conceptual knowledge, procedural knowledge and strategic knowledge.

Conceptual knowledge: presents different static knowledge about facts and concepts related to GBLS gameplay design. This type of knowledge is presented in Fig. 3. Procedural knowledge: includes the set of operations that can be applied on concepts to make transition from one problem state to another. The final type of knowledge concerns the capability that enables game designer to combine its procedural and conceptual knowledge with change adaptation. It can be seen as a general plan of actions in which the sequence of solutions activities is laid down. It concerns knowing how to organize and interpret the information given.

The Automatic Extraction of Gameplay Design Expertise focuses on collecting conceptual knowledge of GBLS gameplay design presented in Fig. 3.

Indeed, as the GBLS gameplay design was presented through ontology [12], enrichment and population of this ontology with information extracted from various sources in automatic is a pertinent solution. It's giving the opportunity to exploit web resources of gameplay that contains necessary knowledge to be acquired.

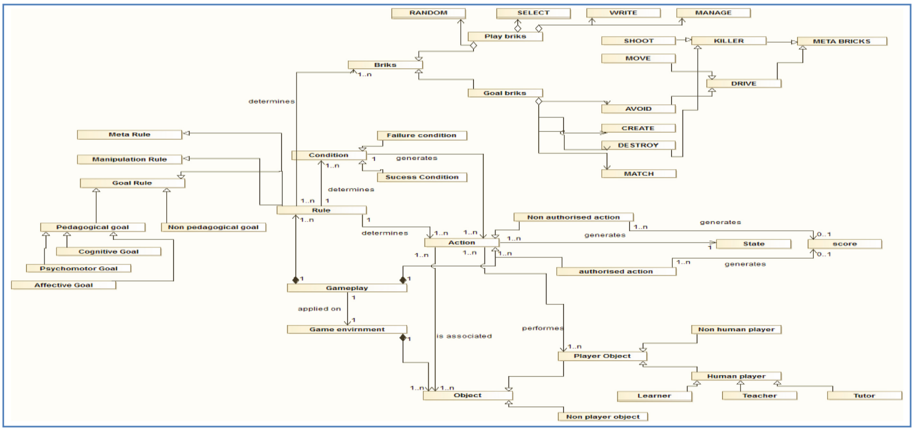

Fig. 3. GBLS gameplay model: conceptual knowledge

4.2 GBLS Gameplay Ontology Population and Enrichment

The attraction of using a semantic technology, to address the problem of gameplay modeling, lies in its potential to associate a semantic network of knowledge related to gameplay description.

These descriptions can then be exploited to add new instances, concepts, relations and rules to the gameplay ontology, providing the developer with new ways and knowledge to design GBLS gameplay.

Two fundamental tasks are addressed to obtain the aforementioned goals, the semantic annotation and the Ontology Learning.

In fact, gameplay descriptions come from multiple resources such as those presented in game instructions, descriptions, and presentation or in GDDs (Game Design Documents).

For this end, four tasks can be identified. The first task concerns initial ontology building. The second task is related to the addition of new instances of concepts/relations into the initial ontology to produce the populated ontology, usually by locating the corresponding object/terms and synonyms in the corpus. The third task is the consistency resolution; it is the responsible for remedying problems introduced by population and enrichment to obtain the consistent ontology. After that, the obtained ontology is exported as RDF file and finally, performance evaluation can be calculated.

Figure 4 depicts a typical Ontology Learning process that we will describe in details in the following sections.

Corpus construction The corpus is composed of GBLS gameplay descriptions collected from many resources as game instructions presented in social network e.g. facebook, Game Design Documents….

For that aim, we select GBLS designed in different periods to limit the impact of technological change on the results that may be obtained. Also, we choose GBLS with single players and GBLS with graphical outputs. Figure 5 presents GBLS description corpus.

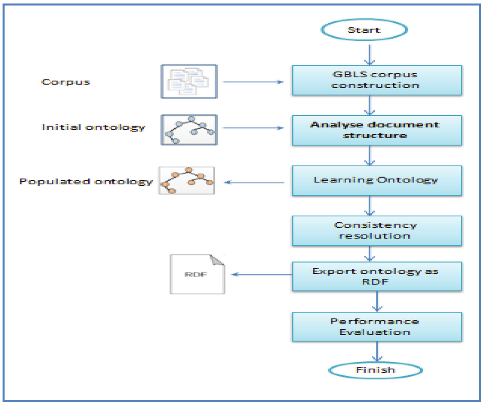

Fig. 4. Ontology learning process

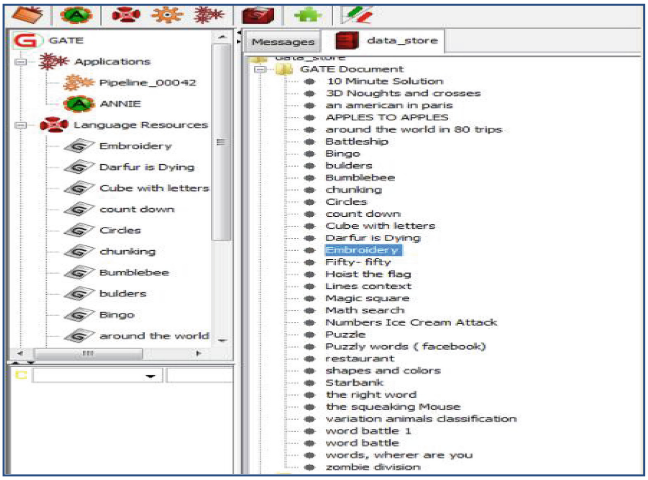

Fig. 5. GBLS Gameplay corpus

Initial gameplay ontology The formal representation of concepts, relationships and instances are described in ontology named initial ontology. Many methodologies are used to design ontology (i.e., [14–16]). All of them consider basically the following steps: definition of the ontology purpose, conceptualization, formalization, and validation. The GBLS gameplay ontology is built according to steps aforementioned; it is presented in our previous work [12]. Figure 6 depicts the initial GBLS gameplay ontology.

Ontology population Ontology population requires (i) an initial ontology that will be populated by inserting concepts and relations, and (ii) an instance extraction engine. For this end we use the information extraction toolkit GATE [17] which performs named entity recognition, syntactic and semantic analysis [18].

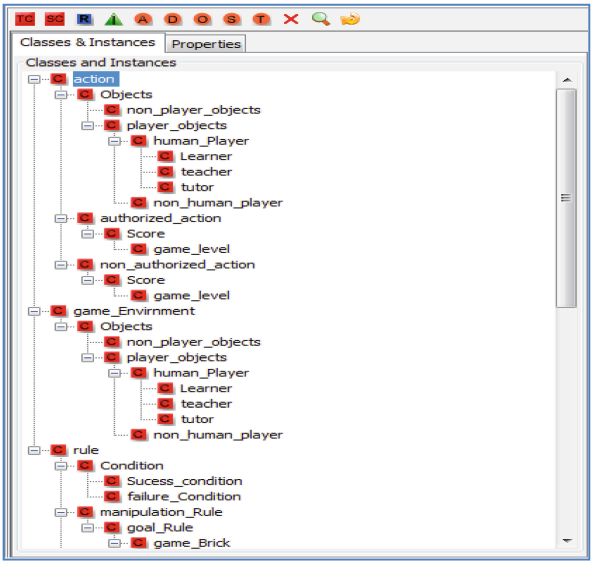

Fig. 6. Extract of Gameplay initial ontology

The extracted concepts and relations are used to populate the GBLS gameplay ontology. The result is an annotated corpus.

The structure of ontology does not change throw ontology population, the concept hierarchy and relations are not modified. What changes is the set of instances of concepts and relations in the domain. The annotated corpuses as well as the ontology population are depicted in Fig. 7.

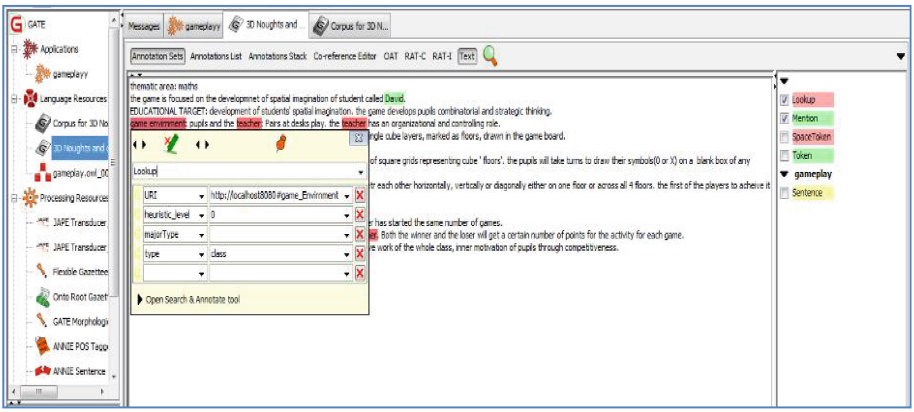

Fig. 7. Example of annotated corpus using the gameplay ontology

Inconsistency resolution This key process constitutes aims to maintain the consistency of the ontology and to eliminate redundancies. Consistency maintenance and redundancy elimination are both automated processes. The first one can be performed with the help of WSMO [19], while redundancy elimination is performed by adding word net plugin in GATE toolkit.

Performance Evaluation Information extraction adopts the typical evaluation measures for text classification tasks being recall and precision, their combination into the Fmeasure, and accuracy. The effectiveness of automatic assignment of the semantic classes is directly computed by comparing the results of the automatic assignment with the manual assignments by an expert [20].

Recall (R) is the proportion of class members that the system assigns to the class. Precision (P) is the proportion of members assigned to the class that really are class members. Fallout (Fal) computes the proportion of incorrect class members given the number of incorrect class members that the system could generate. Ideally, recall and precision are close to 1 and fallout is close to 0. Figure 8 presents the document statistics as the Recall, Precision and Fallout.

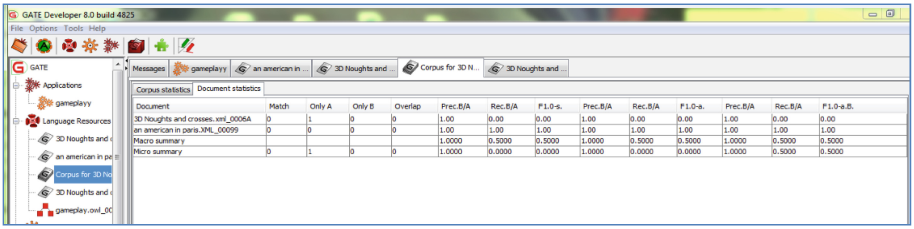

Fig. 8. Performance evaluation of the annotated document

5 Conclusion and Future Work

The principal aim of the work presented in this paper is to define GBLS gameplay knowledge. The idea is to help novice game designer by giving them the opportunity to access, acquire, exploit and share expertise knowledge to produce more attractive and efficient GBLSs.

Our future work will consist on integrating the obtained ontology to the GBLS design frame work that will assist novice game designer through an assistance system where the populated ontology constitutes its expert domain model.

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