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Constructing the virtual Jing-Hang Grand Canal with onto-draw

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ABSTRACT

Constructing virtual 3D historical scenes from literature and records is a very challenging problem due to the difficulty in incorporating different types of domain knowledge into the modeling system. The domain knowledge comes from different experts, including: architects, historians, rendering artists, user interface designers and computer engineers. In this paper we investigate the problem of automatically generating drawings of ancient scenes by ontologies extracted from these domains. We introduce a framework called *onto-draw* to generate semantic models of desired scenes by constructing hierarchical ontology concept domains. Inconsistencies among them are resolved via an iterative refinement algorithm. We implement the onto-draw based ontology design approach and inconsistency removal technique in the virtual Jing-Hang Grand Canal construction project (Chen et al., 2010) and achieve encouraging results.

1. Introduction

1.1. Motivation

Visualizing the minds of different domain experts collaboratively on the same "thing" is the key idea of this paper. In many collaborative designing cases, the crucial problem will always fall into how to balance the viewpoints from different experts. Thus if we can provide a general framework, which can automatically visualize the "things" with all the viewpoints of experts and highlight their conflicts intuitively, it will simplify the designing greatly.

Based on such an idea, in this paper we address the problem of collaboratively constructing 3D historical heritage scenes of the Jing-Hang Grand Canal with semantic techniques. The task to construct the virtual canal of ancient China with spatiality, appearance and historical consistency is complicated. It is very hard for computer modeling engineers to finish alone. The task needs different professional experts to work in collaboration. For example, historians explain historical settings of the canal from related ancient literature, computer engineers build the auto-modeling toolkits etc. The normal approach may employ some manual modeling software or procedural modeling toolkits which are consulted by several experts, e.g. the project of Rome Reborn (Dylla, Frischer, Mueller, Ulmer, & Haegler, 2009). As to the Jing-Hang Grand Canal, this approach may suffer from the following challenges due to the complexity and incompleteness of the canal.

- The most challenging problem may be how to bridge the gap between minds of participators and the real visitable digital 3D scenes with semantic methods. The involved participators normally can only present some features of the scenes with description logic (DL), and obviously are not able to construct those scenes automatically. On the other hand, there are also many approaches (Deussen, Hanrahan, Lintermann, Pharr, & Prusinkiewicz, 1998; Liu, Jiang, & Huang, 2010; Müller, Wonka, Haegler, Ulmer, & Van Gool, 2006) implementing first order logic (FOL) based grammar, e.g CGA grammar in architecture (Müller et al., 2006), L-system in plants (Boudon, Prusinkiewicz, Federl, Godin, & Karwowski, 2003; Deussen et al., 1998), to construct the virtual environments, thus we approximate the challenge of how to bridge those two logics in a general semantic framework.
- Many of those heritages of the Canal are destroyed, experts could only deduce the possible scenes with their own historical and architectural backgrounds, so it contains many controversies due to the incompleteness of the Grand Canal. Then the second challenge is how to detect and resolve the conflicts among different experts on the same

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visual 3D scenes with semantic methods. In a previous similar Rome Reborn Project (Dylla et al., 2009), few works are focused on that issue due to less participators and plenty of objective information for targets. Thus, the solution of this challenge will improve collaboration among varied domain experts greatly and even can be implemented in archeology, e.g. the Virtual Çatalhöyük project (Morgan, 2009)[1].

- The traditional approach normally needs that each expert should be very familiar with the desired target and can describe it systematically, consistently, which is quite a high requirement for the involved designers. That is why the Rome Reborn project needed world famous architects as their consultants. So the third challenge is: with the help of a special semantic framework or toolkit, whether we could proceed with this kind of problem by ordinary designers, who may be not able to provide perfect descriptions for the target.

In order to provide a unified platform and interface to combine different domain knowledge from different experts as well as providing a visual feedback of their designing, we propose an *onto-draw* based framework, which supports that multiple participators design the ontology of a complex problem in visual collaboration.

1.2. Contributions

In this work, we address the research challenges listed above, and make the following contributions:

- We have introduced a novel approach with a hybrid FOL and DL based semantic knowledge system in our onto-draw, by which we can bridge the gap between the minds of participators and digital 3D scenes, then construct heritage scenes automatically. It provides a unified representation for both featured and geometrical knowledge presented by different domain experts, and can depict how those concepts combine in spacial topology, e.g. the spacial combination of architecture components to form an ancient south-east house near the Grand Canal.
- Exploring the semantic relations provided by the above hybrid FOL and DL based semantic knowledge system, we have proposed a formal quantitative definition for the conflict among multiple participators concerning geometrical relations, and we also present the corresponding solution to automatically detect and remove those conflicts under the framework of onto-draw. The presentation of quantitative concepts also provides a beneficial try to evaluate the knowledge set in computable semantic approach.
- We have maintained a scalable ontology design framework which could integrate and improve the designing of desired complex concepts in increments. Thus it will reduce skillful requirements for designers, and enable a stepwise-refinement based design process with the help of a framework.
- We have conducted an empirical user study to evaluate the validity of the onto-draw framework. The results show that onto-draw may be superior to other manual based approaches.

The proposed framework is very general for any task that needs to combine different domain knowledge from different experts. We apply the framework to our specific task of constructing the virtual Jing-Hang Grand Canal that contains as few historical and regional inconsistencies as possible.

1.3. Structure of the paper

The paper is organized as follows. After presenting the background the of digital Jing-Hang Grand Canal and the shape grammar used in our approach in Section 2, related works are given in Section 3, then we present the onto-draw framework, including the definition and general approach in Section 4. Detailed implementation of our onto-draw approach in constructing the Canal is given in Section 5. A quantitative evaluation of our onto-draw engine is presented in Section 6. Some results and analysis of the virtual Jing-Hang Grand Canal are described in Section 7, followed by conclusions and a discussion of future work.

2. Background and primitive knowledge

2.1. Digital Jing-Hang Grand Canal project

Visualizing the destroyed heritages is a challenging task, e.g. the visual Çatalhöyük project (Morgan, 2009) takes about ten years of collaborative work by many experts from different fields, they need to collect the clues regarding heritages and deduce the possible states of destroyed heritages and discuss to resolve their difference of opinion. More recently, the procedural modeling technique was introduced in that task to improve the efficiency of construction, and archived significant results such as the Rome Reborn Project (Dylla et al., 2009). However, a general efficient semantic framework for those heritages virtual recovering is still an untouched research field.

There are many ancient heritages which are damaged or lost in the long history of China. As these heritages are not well preserved (some even have been destroyed completely), traditional modeling approaches such as 3D scanning or image based modeling cannot be used. However, there will be significant research and social impact if these ancient scenes can be realistically "drawn" to us. This "drawing" process includes not only reconstruction of realistic scenes in 3D but also the rendering of scenes to the user. This seems an impossible task, fortunately there are many historical literatures describing those heritages, and the existing heritages could also provide many clues regarding those destroyed. This paper investigates whether it is possible and how to "draw" these heritages using varied domain knowledge from multiple experts.

In our heritage preservation project, we construct the virtual Jing-Hang Grand Canal both with the 3D models and historical annotations. The Jing-Hang Grand Canal, shown in Fig. 1, is the longest ancient man-made canal in the world. It starts from Hangzhou and ends in Beijing with a total length of roughly 1100 miles. The oldest parts of the canal date back to the 5th century BC, different parts of it were finally connected during the Sui Dynasty. The Grand Canal system represents a remarkable achievement of imperial Chinese hydraulic engineering. It connects the political center of the empire in the north with the economic and agricultural centers of central and southern China.

The Jing-Hang Grand Canal passes through almost half of China from north to east. The environment (including architecture and culture) along the canal varies a lot due to regional differences. The virtual canal that we build should obey the spatial consistency, appearance similarity as well as historical consistency with the literature. In other words, scenes and settings of the virtual canal generated by a computer system should match and be compatible with its corresponding time and regional characteristics.

[1] http://www.catalhoyuk.com/.

Fig. 1. The map of Jing-Hang Grand Canal with typical heritages in nearby cities, which are symbols of some ancient dynasty. The culture, architecture, commerce, and even the legend of the cities near the Canal are strongly related with the Canal.

2.2. Shape grammar and FOL in our approach

Before presenting the ontologies in our Canal project, we will first introduce the basic shape grammar implemented in our approach. All the geometry objects in our shape grammar are within a boundary box shown in Fig. 2, and we also define six spacial relationships for the combinations, that are "Top (T) of the object", "Down (D) of the object", "Left (L) of the object", "Right (R) of the object", "Front (F) of the object" and "Back (B) of the object". With these spacial control terms, experts could present their own domain knowledge on the spacial combinations of the scenes easily. For example, the roof of a Southeast Chinese vernacular house may constitute two components: a roof center and a roof body. The roof center, shown in Fig. 5, is just on the top of the roof body, then we can express the roof as follows:

$$\text{Roof} = [v_1]Tv_2$$

where v_1, v_2 are the components defined in the ontology example in Fig. 5. In addition, our shape grammar also supports the quantitative control terms which could scale the boundary boxes of the geometry objects in each axis (X,Y,Z, in Fig. 2) and transform the coordinate of the objects based on an absolute coordinate or a relative coordinate. The detailed implementation may refer to our previous works (Liu, Xu, Pan, & Pan, 2006) and Wonka's CGA shape grammar (Müller, Wonka, Haegler, Ulmer, & Gool, 2006). A more complex example to express the house w_1 in Fig. 5 is given as follows:

$$\begin{aligned} w_1 =& [[v_1]Tv_2]T[[v_5]L[[[v_4]Tv_6]T[v_4v_7v_4]D]F[v_8]R[[[v_4]Tv_6] \\ & \times T[v_4v_7v_4]D]B]D \end{aligned}$$

In the above example, '$v_4v_7v_4$' means that the three objects are placed aligning with the X axis.

The essential of our shape grammar is spacial description logic and obviously the participators cannot enumerate all the possible combinations in practice. So we use some L-system based grammar rules to generate the sequences of combination, and those recursive L-system based grammar rules consist of the FOL based semantic knowledge library U.

An example of U [2]is presented as follows:

$$\begin{aligned} U = \{ & L_1(v_{window-wall} :: v_{window-wall}|v_4), \\ & L_2(v_{window-wall} :: v_{window-wall}|v_4|v_7), \\ & L_3(v_{roof} :: v_1|v_2), \\ & L_4(v_{house} :: v_{house}|v_{roof}|v_{window-wall}|v_4|v_{window-wall}|v_4), \\ & \ldots \} \end{aligned}$$

Here $v_{window-wall}$, v_{house}, v_{roof} are temporary components in logic,[3] after recursive generating, they will generate a final sequence, which is all constituted by the terminal components $v_1, \ldots, v_8$ of w_1 in Fig. 5.

[2] In this sample, we omit the spacial control terms.

[3] $v_{window-wall}$, v_{house}, v_{roof} are corresponding to v_9, v_{11}, v_{10} of programmers' rules in Fig. 5.

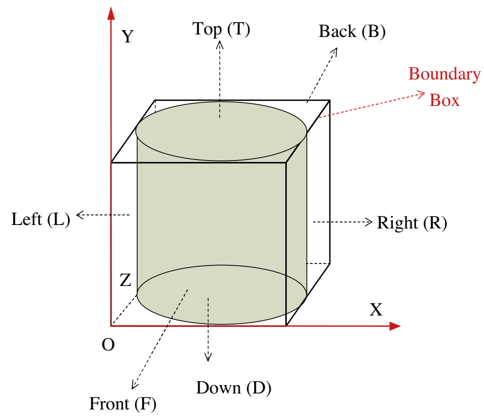

Fig. 2. The boundary box and coordinate of a spacial object in onto-draw modeling, and it also shows the six spacial control terms in our shape grammar.

The rules include two kinds of terms: the nonterminal component (or term) and the terminal component; The nonterminal components could be replaced by the components on the right side of its rule. For example, in $r_1(v_9 :: v_9|v_4)$, the components v_9 is the nonterminal component and could be replaced by its right side $(v_9|v_4)$.

The aforementioned recursive rules are subjectively obtained from examples by domain experts; As those rules will generate infinite combinations with random recursing, the knowledge structures cannot guarantee that their recursive results will all lead to the desired combination sequences (or the correct scenes with proper spacial relationship). So in our approach we hybridize both the FOL based rule system and the DL semantic technique, we iterate FOL rules to generate possible combination sequences and use DL semantic descriptions to verify those sequences to obtain the desired scenes automatically. Every participator could present his/her viewpoint on the correct combinations and characteristics of their targets with DL based semantic knowledge structure individually, e.g. the roof should be under the wall, the wall should be of white color etc., and then our onto-draw system will auto-implement those semantic descriptions in the generated sequences.

2.3. Inconsistency in collaborative designing with multiple participators

To construct a virtual Jing-Hang Grand Canal that is close to what it was, we need to combine the domain knowledge from experts in different domains. These experts have different domain knowledge for different fields of the Canal and they are collaborating for a common goal of realistically constructing the virtual Jing-Hang Grand Canal. We have experts from five different fields involved in the ontology and onto-draw design process. They define ontologies about the Canal from their own professional viewpoints. Then our onto-draw system unifies their knowledge together to generate the final drawing. The roles of the five domains are presented as follows:

- *Architects for ancient China architecture* present all the reasonable construction and combination knowledge for various houses, towers, bridges,and docks in different cities close to the Grand Canal.
- *Historians* define ontologies for all the elements with specific historical background, for example, realistic scenes of carrying cargoes into boats in docks in the Qing dynasty. The historical elements include culture, commerce, history stories and daily life of the ancient age.
- *Rendering artists* design drawing styles and drawing details for the basic elements of the virtual canal including the rendering of viewpoints of the scene and the painting styles, e.g, the traditional Chinese paint style shown in Fig. 8 (a) and (b) or the normal 3D rending style in Fig. 8(c)–(f).
- *Programmers/ontology experts* present the ontologies for transferring the canal based domain knowledge into the semantic descriptions, linking corresponding mapping relationships among different domains. They implement the onto-draw engine, which can parse all the concept domains and produce instances of the virtual Jing-Hang Grand Canal. The ontology of programmer uses the FOL based grammar presented in the above section to generate the basic geometrical scenes automatically.
- *User Interface (UI) designers*: The virtual canal is part of the Chinese digital heritage project, and it will be deployed in the Jing-Hang Grand Canal museum and be exhibited to visitors. So we need UI designers to present the ontologies for visitors to virtually explore the Jing-Hang Grand Canal. As the constructed scenes are semantic, every components may have an annotation list. A complex scene will attache with huge number of annotations, it is not proper and possible to display all those semantic annotations to final users. So we need the UI designers to decide which components' annotations should be displayed to the final users. Moreover, the original annotations that auto-generated from other domain experts' ontologies may be fragmentary, which means they mainly focus on the annotations of basic components. Sometimes, we may need to annotate a special scene or combination which is not covered by other domain experts' ontology or specified by the users, then the UI designers can specify in which condition the objects may link with a specific annotation.

Inconsistent knowledge among different participators is one of most popular problems in collaborative designing. In our case, most of the conflicts occur between programmers and other domain experts. The first typical conflict is *combination inconsistency*. As programmers focus on designing the FOL based production rules to generate the scenes, the recursive generation via those rules sometimes will produce indeterminable combinations which will conflict with descriptions presented by architects, e.g. if we produce the instances only with programmers' $r2(v9 :: v9|v4|v7)$ in Fig. 5, and may generate a sequence: $v4v7v4v7$ which means the combination of "shop-wall,column,shop-wall,column", however this may conflict with the architect's knowledge that the column $(v7)$ should not lie on the borderline of the shop-wall-columns combinations. So the right combinations need to include another programmers' rule, $r1(v9 :: v9|v4)$, to obtain the sequences, such as $v4v7v4v7\ldots v4$.

Another conflict is *attribute inconsistency*. The general working process of programmers is to construct the scenes randomly guiding with those production rules. During the processing, the attributes of each component is either random setting or null, e.g. programmers may not be concerned about the material of the roof in ancient Chinese architectures, and then the attribute of material for roofs in their generating results may be set as null. To generate varied unrepeatable scenes, the color of the components may be selected randomly from a valid range, so the conflict may occur once the stochastic decision is inconsistency with the descriptions of other domain experts. We call this inconsistency condition as *attribute conflict*.

3. Related work: from basic draw to onto-draw

The basic way of drawing should be the manual drawing with the modeling software such as the Sketchup, AutoCAD. Designers can draw what they think exactly via this method, however, the designing process is tedious, non-collaboratively and the results of drawing strongly depend on the knowledge and ability of designers.

Physical model based techniques have been developed to draw scenes controlled by mathematical models, e.g. the physical model of snow falling (Fearing, 2000). In these methods, users can draw scenes by simply choosing several model parameters then the system automatically generates constructed drawings. The drawback of these methods is that drawing results of scenes that can be generated by physical models are quite limited, and some scenes are very hard or impossible to be built using physical models.

Drawing 3D models from the data collected by capture devices, such as images (Jiang, Tan, & Cheong, 2009; Quan et al., 2006), videos (Pollefeys et al., 2004), cloud points (Addison & Gaiani, 2000; Nan, Sharf, Zhang, Cohen-Or, & Chen, 2010), or combinations of those above data (Fruh & Zakhor, 2001; Vanegas, Aliaga, Benes, & Waddell, 2009,) could construct the scenes veritably, it is also a popular research hotspot. However, those approaches may suffer with either limitation in small scale scenes or huge expensive costs, and the most important problem is that they all need to scan or ''see'' the real scenes, which may be impossible in our Grand Canal digital heritage project.

Drawing with the control of nature language (Coyne & Sproat, 2001; Johansson, Berglund, Danielsson, & Nugues, 2005) is another approach. However, these systems are limited in two aspects: it is hard to guarantee the coherence of logic in natural languages and ambiguities inherent in languages make it hard to describe some target scenes.

Drawing with grammar systems (Aliaga, Rosen, & Bekins, 2007; Müller et al., 2006; Whiting, Ochsendorf, & Durand, 2009) could be viewed as an advanced physical modeling technique, e.g. In Emily Whiting et al.'s approach (Whiting et al., 2009), it allows users to draw their houses with the grammar system. This method normally employs FOL based grammar, for example the L-system or CGA shape grammar system, to control the drawing process and randomly rewrites the nonterminal terms in rules recursively to generate a lot of drawing results, then manually chooses the right ones as the output. However, as mentioned in the above section, these systems usually cannot provide an intuitive to control the generation process, and thus the sole FOL based rule systems are not proper for knowledge representation in collaborative design cases.

To overcome the problems of grammar systems, semantic techniques may be the most possible approaches. There are many works which try to implement semantic techniques into the digital heritage applications (Isaac et al., 2009; Ruotsalo, Aroyo, & Schreiber, 2009; Tzouveli, Simou, Stamou, & Kollias, 2009). One of the most used applications is semantic annotation, which employs ontology to ease the extraction of structured knowledge from natural language description (Tzouveli et al., 2009), or generate annotations for complex multimedia, e.g. M3O (Saathoff & Scherp, 2010), COMM (Bocconi, Nack, & Hardman, 2008)[4]. Since they conceptualize the described domain and so they can offer the eligible concept to be selected for semantic annotation. However, those techniques can only add semantic annotations on those existing objects, they also do not support the spacial logic in geometrical construction, thus cannot be used to ''draw'' the scenes. Another related semantic technique is semantic drawing (Farrimond & Hetherington, 2005; Liu & Xu et al., 2006; Liu, Xu, Zhang, & Pan, 2006; Liu, Xu, Zhang, & Pan, 2008; Luca, Véron, & Florenzano, 2007), in which all components in the scene are represented with semantic descriptions and also can be associated with annotations. Although this method also employs the FOL based grammar to generate the scenes, it focuses on easing the designing of FOL based generation rules by wrapping basic geometrical elements, e.g. point, line, box etc. into semantic components, e.g. window, wall, roof etc. Few emphases are concerned with detecting and reducing of participators' conflicts with semantic methods, which are quite important to construct the scenes with multiple domain experts collaboratively.

There are multiple domain experts involved, then they may use different terminologies on the same concept. So the ontology alignment (Chen, Tan, & Lambrix, 2006; Isaac et al., 2009; Ponzetto & Navigli, 2009) should be mentioned here, which may be used to align the concepts presented by different domain experts. Most of the current works, e.g. Isaac et al. (2009), do not perform well in specific digital heritage applications, for they may strive for generality and need an accurate concept database corresponding to the target digital heritage. In our case, the concept database for culture of Grand Canal are almost empty, so we have to adopt another approach to solve the alignment problem.

As mentioned in the previous section, an ideal drawing system should be capable of (1) incorporating knowledge from different domains, (2) providing a platform for the collaboration of different experts and (3) auto-generating drawings using as little user input as possible. However, none of existing systems meet all the three requirements. Furthermore, current semantic techniques cannot solve these problems in our case directly. To achieve the above goals, we propose an ''onto-draw'' framework based on a hybrid of FOL and DL grammar systems.

4. Onto-draw: definition and approach

4.1. Ontology for drawing models

Traditional understanding of ontology (Gruber, 1993; Guarino, 2004) includes a series of categories, components and relations intended as systematic descriptions covering all instances of a specific concept.

In this article, ontology in ''drawing'' is used to reconstruct various 3D objects in the virtual scene. This means drawing virtual scenes can be regarded as establishing the ontology from the literature for each scene and generating its instances. For example, when constructing a virtual Sui dynasty street near the Grand Canal, models for bridges, houses and towers in the scene may vary, but all their styles and shapes should be consistent with the historical background and regional features.

Formally, the ontology for drawing scenes is a four-tuple (Liu et al., xxxx), $C = \langle D, W, R, V \rangle$, where D represents the domain of objects, e.g. the southeast Chinese architecture domain, the north Chinese tower domain. It also implies a classification of objects in the virtual scene. V is the related entities set (vocabularies) in

[4] http://comm.semanticweb.org/

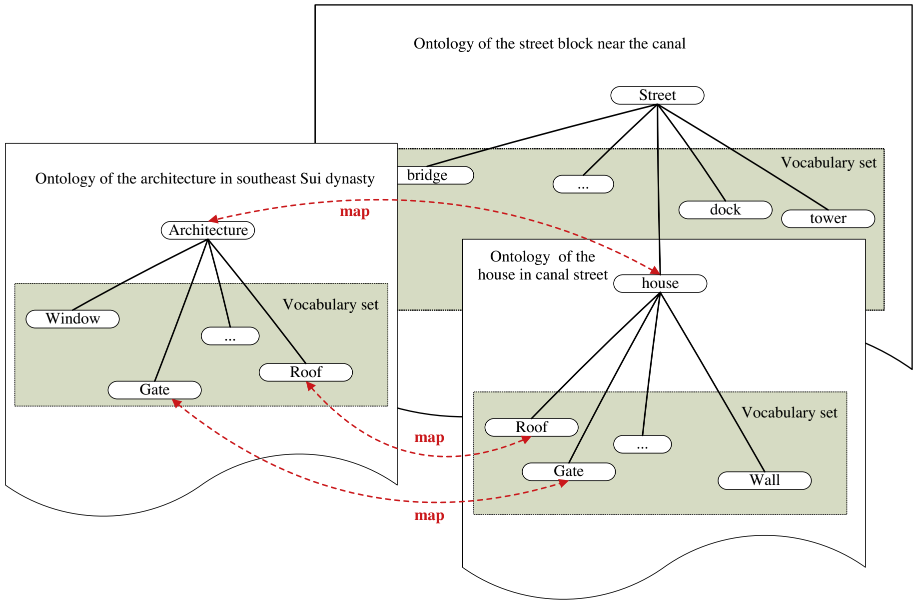

Fig. 3. The hierarchical ontology in *Onto-draw*.

an object ontology. It should include all the sub-components of the represented object domain. W is the domain space and it consists of all the instances covered by the domain, and involves possible states of affairs (or worlds) corresponding to mutual relations among entities. R includes two sets, one contains the intrinsic characteristics of the current ontology concept, and the other contains construction rules for modeling (or drawing) instances of current ontology domain. The construction rule set can be viewed as the relation set established between entities and instances of a specific domain, e.g. in what kind of combination relation R that the entity set V can constitute the architectures W of the domain D. In our onto-draw system, the construction rules of R can be approximated as the FOL based recursive rules and DL based rules, and R can also be called domain knowledge.

As complex scenes normally consist of multiple hierarchical concepts, we construct a hierarchical ontology domain by allowing the elements in the vocabulary set also to be a concept of an ontology domain. This is significantly different from previous work (Liu et al., 2008). For example, Fig. 3 shows several ontologies in the virtual Grand Canal. The vocabulary set of the street ontology includes the bridge, house, dock, tower etc. All these concepts are ontology domains, which are represented using their domain identifier D, vocabulary set V, instance set W and domain knowledge R. Then a complex ontology can be synthesized by many simple hierarchical ontology domain concepts.The ontology here may be referred to as high-level structured semantic annotations of concepts involving in the Grand Canal. Each concept is organized as the unified form of four-tuple, which will enable our system to exchange and share the knowledge extracted from literature or subject experiences of domain experts.

4.2. Formal Definition of onto-draw

The hierarchical ontology architecture can simplify the design of complex ontology. However it may introduce inconsistencies because ontologies created by different domain experts may have conflicts. The onto-draw should be able to identify and resolve these inconsistencies. In this section, we introduce several key operations in onto-draw and the definition of inconsistency.

4.2.1. Mapping

Inconsistencies among ontologies mostly occur in corresponding domains that describe the same concept. We call the relationship between corresponding concept domains "mapping". If ontology C_1 is in mapping relationship with ontology C_2, denoted as $maps(C_1,C_2)$, then

$$maps(C_1,C_2) \to \exists C(D,W,R,V), \quad v = C_1 \cup C_2, v \in V$$

This definition states that if C_1 and C_2 are in a mapping relationship with each other, the union concept of C_1 and C_2 can be viewed as a vocabulary element in higher level ontology C. For example, in Fig. 3, *house* in the ontology of street and the *architecture* ontology, *roof* in the ontology of house and architecture, *gate* in the ontology of the house and architecture are in mapping relationship.

If C_1 is mapping with C_2, w is an instance of ontology $C_1(w \in W_1)$, then we call instance w *semantically related* to ontology C_2.

$$maps(C_1,C_2), w \in W_1 \to w \text{ is } \textit{semantically related} \text{ to } C_2$$

4.2.2. Part-of and consistency

When generating ontology instances, the sub-domains (vocabularies) will firstly generate their own instances and then they are combined into the instance of parent-domain using the domain knowledge R. Before detecting inconsistencies between ontologies, we define the operation of decomposing an instance. This is the *Part-of* operation.

Let $C_k(D_k,W_k,R_k,V_k)$ be a sub-domain of Ontology $C(D,W,R,V)$, where $w \in W,\ C_k \in V,\ Part-of(w)_{C_k}$ is defined as

$$Part-of(w)_{C_k} = \{v_1, v_2, \ldots, v_i\}, \quad v_i \in w, v_i \in W_k$$

Here C_k is a sub-domain of the C, so the v_i should belong to both the instance w and the C_k's instance set W_k. If C_k is not a sub-domain of C,

$$Part-of(w)_{C_k} = \{\cup Part-of(w)_{C_j} | C_j \in V, maps(C_j, C_k)\}$$

Obviously, if C_k is a concept that contains C, or cannot find any sub-domain mapping with C_k in V, $Part-of(w)_{C_k} = \phi$.

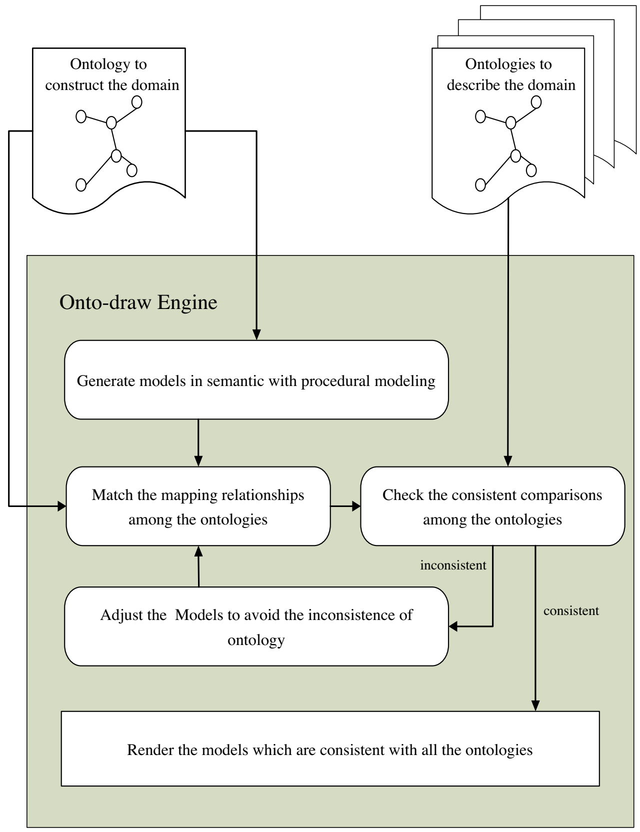

Fig. 4. The general approach for *Onto-draw*.

We introduce the concept of *consistent set* and *conflict set* (Chen, Chen, & Zhang, 2007) to define the onto-draw.

Let w be an instance of $C(D,W,R,V)$, to an ontology $C'(D',W',R',V')$, the w's consistent set with respect to C' is defined as

$$consistent(w)_{C'} = \{\beta | \beta \in Part-of(w)_{C'},\ \forall r \in R',\ \beta \text{ satisfy } r\}$$

And the w's *conflict set* with respect to C' is defined as

$$conflict(w)_{C'} = \{\beta | \beta \in Part-of(w)_{C'},\ \exists r \in R',\ \beta \text{ unsatisfy } r\}$$

βsatisfy r means that the component β can fit the domain knowledge r. And there are two unsatisfied conditions in our onto-draw:

- Attribute inconsistency, which means that the attributes generated in instances are in conflict with the corresponding knowledge rules, e.g., the rule $r(v_i.Attribute_1 = S)$ will be conflict with the instance $v_i.Attribute_1 = Q$.
- Combination inconsistency, which means that the combination generated in instances are in conflict with the corresponding knowledge rules, e.g., the combination rule $r(P = v_1, v_2, v_3)$ will be conflict with the combination in instance $P' = v_3, v_3, v_1$. And more examples are given in Section 5.

If $conflict(w)_{C'} = \phi$, w is consistent with ontology C', otherwise we call w inconsistent with ontology C'.

4.2.3. Onto-draw

The onto-draw should support multiple hierarchical ontologies and avoid inconsistencies among them. Our onto-draw is defined as follows:

$C(D,W,R,V)$ is the ontology of the scene that we need to draw, $C_1, C_2, \ldots, C_n$ are the context-sensitive domains with C, the onto-draw is a special generalized function (Liu et al., 2008), denoted G, $w = G_\rho(V)$, $\rho \in R$, having.

- $w \in W$
- $\forall w(w = G_\rho(V))$, w is consistent with ontology $C_1, C_2, \ldots, C_n$.

The onto-draw is defined as a function of the ontology of $C(D,W,R,V)$, it can produce instances of the ontology domain C and prevent any inconsistencies with ontologies $C_1, C_2, \ldots, C_n$.

In our problem, we aim at reconstructing scenes at a specific historical time instead of a long period. So we need not model the evolving behavior of ontologies, nor do we need to model inconsistencies over time (Haase & Stojanovic, 2005).The concept alignment may be involved in part of the inconsistency problem in onto-draw, for the onto-draw should detect the inconsistencies between the concepts aligning on the same essence instead of the same concepts in names.

4.3. General approach for onto-draw

The onto-draw can be implemented with an onto-draw engine shown in Fig. 4. The input to the onto-draw engine includes a series of ontology descriptions: one set contains the FOL based ontologies (or rules) to construct the instances and the other one contains DL based ontologies to summarize the target domain.

The onto-draw engine will first employ the FOL based rules such as the U in Section 2.3 to generate several instances of the target domain, that means it rewrites those non-terminal terms in FOL based rules recursively randomly to construct the basic geometrical combinations of desired scenes, which is similar with those procedural modeling approaches (Liu et al., 2010; Müller

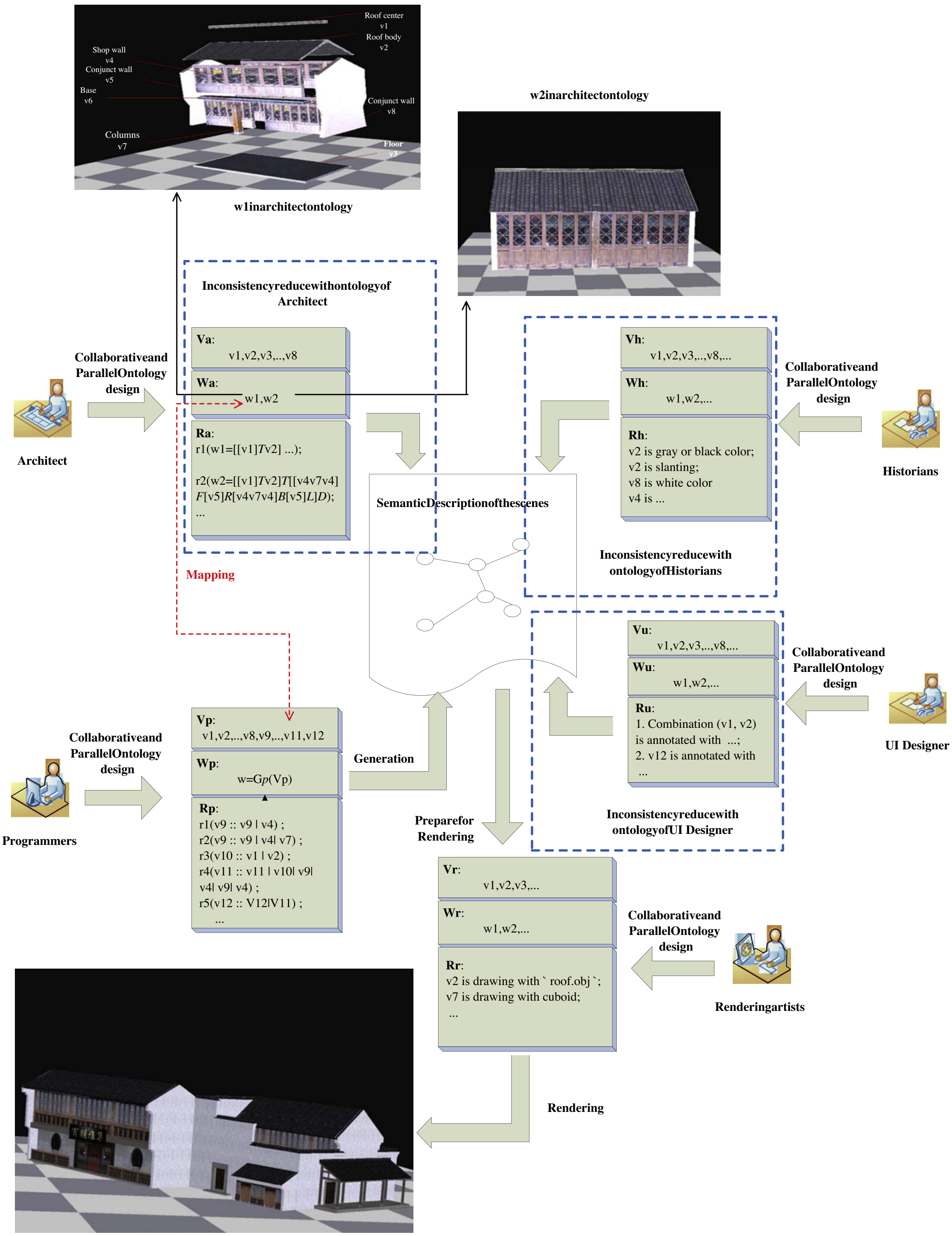

Fig. 5. Ontology examples from multiple domain experts. Here, the means of $w_1, w_2, \ldots, w_8$ are shown in the left-top figure, and w_9 is the window wall component, v_{10} is the roof component, v_{11} is the house (which is also mapping with the instances w_1 and w_2 in the ontology of architect), v_{12} is the urban block. The sample ontology of the architect presents a southeast Chinese ancient architecture domain with only two rules, which indicate two styles of houses shown in the top of this figure. The hierarchical concept domains should be established by the participators previously. Then our onto-draw engine could proceed by mapping relationships between the instances and ontologies automatically, detect and reduce the inconsistencies.

et al., 2006). As those production based rules cannot guarantee the rightness of instances, the onto-draw engine decomposes components of these instances via the *Part-of* operation and find the mapping relationships with other input ontologies. Then onto-draw engine will detect inconsistencies among the semantically related components and ontologies (including all the sub-domains). If there are inconsistencies, it will revise parts of the instance where inconsistencies occur. The onto-draw engine will iterate the above process until there are not any inconsistencies in generated instances. Finally, the engine sends generated instances of target domain to the renderer, and outputs the final virtual scenes. A sample instance generated by the engine is shown in Fig. 6, which contains the semantic descriptions (characteristics or features) of components in scenes, basic geometries and combinations of components. Then renderers could design different drawing styles for the instances, e.g., they can design a toolkit to convert semantic instances to X3D[5] formats and draw scenes with X3D rendering engine or other game engines, such as OGRE.[6] The instances generated by onto-draw are semantic, because each part of the instances is produced by well semantic-structured ontologies, i.e. the four-tuple. Then the instances are naturally semantic annotated, it will be quite easy to carry out further semantic retrieving, searching with geometry, manipulating via historical or spacial parameters, aligning with other heritages, even rendering with different styles.

5. Building virtual canal with onto-draw

5.1. Multiple participators in hierarchical Jing-Hang Grand Canal ontology design

Our onto-draw system can unify knowledge from five domain experts to generate the consistent final drawing. In the following, we briefly describe the processing of integrating the knowledge of five experts by the sample shown in Fig. 5.

- *Ontology of Architects.* In the example of Fig. 5, we present a sample ontology $C_a(D_a,W_a,V_a,R_a)$ from architect to define the vernacular house in Southeast China. The example only contains two instances of the Southeast vernacular houses (w_1 and w_2).[7] and two combination rules for the domain.[8]
- *Ontology of Historians.* In the example, historians present a rule that the roof body (v_2) in southeast Chinese ancient architecture is gray or black in color, based on the history literature. When designing the ontology for the scene in the North of China, they may present the rule that the roof is golden or red in color.
- *Ontology of Rendering artists.* The ontology of rendering artists normally presents the basic geometry of components and some complex components such as the roof body, which may be represented by the point-mesh files, e.g. the 'roof.obj' in example.
- *Ontology of Programmers.* The ontology of programmer uses a FOL based grammar, which could also support the quantitative control terms (scaling the boundary box) and spacial control terms (shape grammar in Section 2). In our approach, the onto-draw engine employs the ontologies of programmers, randomly selects the rules, e.g. the programmers' rules in Fig. 5, and recurs those selected rules to generate semantic scene instances.
- *Ontology of UI designers.* As the end users may be varied, the UI designers will design the annotations with the different requests of end users, e.g. the scene for historical users may focus on the annotation of the typical events and backgrounds, while the scene for architectural users may focus on the annotations of the layout and combination of each components. As shown in Fig. 5, rule one of the UI designer, all the combinations of (v_1, v_2) will be linked with the annotations defined in those rules automatically, when the huge scene is generated. Then the onto-draw engine will automatically check the scene and attach these annotations when outputting the final results.

As there are five kinds of participators involved in the ontology design, we adopt the multi-level projection ontology design method (Liu et al., 2008) to build hierarchical Grand Canal ontologies in collaboration.

In onto-draw engine, we also adopt a category tag method to annotate the characteristics proposed by the domain experts, that is we add an additional tag for the characteristics in ontologies, e.g. Fig. 5 in historians' ontology, rule 'v_8 is white' is tagged with a regional tag, for v_8 may be red in North of China.

The ontologies designed by these experts are specified with four kinds of tags, which are *regional characteristic*, *historical characteristic*,*architectural characteristic* and *normal characteristic*. Regional tags identify in which regions the attributes of the tags are valid, historical tags identify the valid period of the corresponding ontological attributes, architectural tags identify the valid styles or combinations of architecture, and the normal tags emphasizethat the ontological attributes are always valid.

5.2. Semantic representation for the scene instance

The onto-draw engine will represent the scene with a semantic description. Fig. 6 presents a sample of the semantic description. Obviously, the shape grammar which represents the spacial relationship of components could be easily implemented by the tree-structural XML description. And it also supplies the attribute tags which could represent the values defined in the ontology (such as "the color is gray" etc.).

5.3. Automatical inconsistency detection and reducing

Before designing their ontologies collaboratively, all the domain experts should discuss together to confirm the hierarchical ontology concepts, e.g. the hierarchical component relationship map in Fig. 3, involving the desired scene. Then they could design their domain ontology related with these unified hierarchical concepts individually. Although the aim of this process may be similar to the ontology alignment (Chen et al., 2006; Ponzetto & Navigli, 2009), it is easier that it only limits structural information concepts (Euzenat & Shvaiko, 2007).

With the hierarchical ontology concepts (it also refers to the *D* in our ontology definition), the onto-draw engine can map the concepts described in ontologies and the corresponding component instances automatically.

The inconsistency detection in our onto-draw is established on the automatically "semantically related" relationship detection, the onto-draw engine will find all the "semantically related" relationships and match them with the knowledge rules of all the ontology designers.

As to the inconsistency reducing, there are two conflict (un-satisfy) conditions in the consistency checking process. For the attribute inconsistency, the onto-draw will use the attribute given by the knowledge rules to replace the instances' that reduce the inconsistency, e.g., the conjunct wall in Fig. 6 is red in color, and it conflicts with the ontology defined by a historian (Fig. 5). When proceeding the inconsistency detection and reducing, onto-draw engine will replace it with "white" for the color attribute. The reducing for combination inconsistency is much more difficult,

[5] http://www.web3d.org/x3d/.

[6] http://www.ogre3d.org/.

[7] In the real case, there may be many more instances in the instance set *W* or even innumerate instances.

[8] Both two rules in the example describe the combination of houses, in practice implementation, it may contain the combination for a group of the components in *V* or some attribute description for the components similar with the example of historian's ontology.

```
<Urban name = "Southeast_Urban_near_Canal">
    < Block>
        <hasTopology rdf:resource = "Topology.owl#block_southeast"/>
        <hasRoad rdf:resource = "Road.owl#road_in_block_southeast"/>

        <House name= "Southeast_House_1023">

            <hasCombination>
             <!---To identify the combination more clearer, -------------->
             <!---we use the symbols in the ontology example, ---------->
             <!---that is "[[v1]    Tv2] T[[v4] F[v5] R[v4v7v4] B[v5] L]D " -->

               <Component Layout="Top">
                  <Component Layout="Top">Roof_Center_2131</Component>
                  <Component >Roof_body_3207</Component>
               </Component>
                     …
               <Component Layout="Left"> Conjunct_wall_1124</Component >
               <Component Layout="Right"> Conjunct_wall_1124</Component >
                     …
            </hasCombination>
                     …
            <Roof_Center name="Roof_Center_2131">
                     …
            </Roof_Center>
            <Conjunct_wall name="Conjunct_wall_1124">
               <hasRender rdf:resource="Render.owl#cw_southeast"/>
               <hasBoundary>
                  <BoundaryType>Box</BoundaryType>
                  <BoundaryWidth>3.2</BoundaryWidth>
                  <BoundaryHeight>7.5</BoundaryHeight>
                  <BoundaryThickness>0.3<BoundaryThickness>
               </hasBoundary>
               <hasColor>
                    <BodyColor>Red</BodyColor>
               </hasColor>

            </Conjunct_wall>
        </House>
        …
    </Block>
</Urban>
```

Fig. 6. A sample semantic description of the scene for instance, here the limited page, we omit the complex control tags for those components.

once the combination inconsistency is detected, e.g. the combination of component ‘*Southeast_House*_1023’ is

$$[[v_1]Tv_2]T[[v_4]F[v_5]R[v_4v_7v_4]B[v_5]L]D$$

it is conflict with the r_2 in architects’ ontology. Our onto-draw will mark the component with inconsistency in the scene semantic description, backdate the generation rules (normally defined by the programmers) for the conflict components, and then choose other rules or change the random parameters to regenerate the component. Here for the inconsistency between ‘*Southeast_House*_1023’ and r_1, the onto-draw will backdate the instances generated by the architects’ rule $r_1(v_9 :: v_9|v_4)$ and then use another rule $r_2(v_9 :: v_9|v_4|v_7)$ to re-generate the instances.

5.4. Onto-draw approach in constructing virtual canal without inconsistency

After collecting ontologies from different experts, we build an onto-draw system, which is based on the core onto-draw algorithm (see Algorithm 1, onto-draw generation algorithm for Jing-Hang Grand Canal) to produce instances of the canal. Before executing the algorithm, mapping relationships among all the concept domains are first identified.

In our algorithm, the input ontology C is a canal ontology with high level semantics, and $C_1, C_2, \ldots, C_n$ are detailed characteristics of Jing-Hang Grand Canal. We also use a threshold θ to control the number of inconsistencies of the instance our onto-draw system can tolerate. $F_\rho(V)$ is a function (Liu et al., 2008) to produce an instance of the ontology $C(D,W,R,V)$ with the vocabulary set V and knowledge subset ρ, $\rho \subseteq R$.

Here we use two counts to record the number of inconsistencies in generated instances. One is *incons_norm*, which is the number of inconsistent attributes whose properties are marked with “*normal*”; the other is *incons*, which is the number of inconsistent attributes with other tags, e.g. “*regional characteristic*” or “*historical characteristic*”. As the *normal* tags are obligatory in validation, our algorithm requires *incons_norm* = 0 as one of the terminating conditions. For simplicity and efficiency concerns,[9] we slack the constraint for other inconsistency (e.g. historical and reginal factors), so we add a control threshold θ as the terminating condition ($incons \leqslant \theta$). We also add the control parameters *max_try* to ensure the algorithm will be terminated after large iterations.

One more thing to clarify is that in step 4, the algorithm does not always generate a new instance from the ontology C, it may only regenerate the inconsistent parts to increase the efficiency of the onto-draw system. When the inconsistency appears, we adopt a more efficient approach to regenerate only the inconsistent components by function $w = adjustment(w, incons, incons\_norm)$. In this function, if $incons = 0$ and $incons\_norm = 0$, it will not make any changes in the input w, otherwise it will iterate the conflicts in input w, try to regenerate each of the inconsistent components, then be re-validated, and details are given in

[9] If it is enforced that there are not any conflicts in the result instance, the onto-draw processing may need a huge generation and searching space due to the design of ontologies.

Table 1
Score criteria in user study.

Max score	Criteria	Detailed description
3	Overall rating	(I) Looks like the ancient Chinese scene in Sui Dynasty (0–0.3: completely not; 0.3–0.6: median; 0.6–1:totally yes) (II) Contains enough details of the ancient Canal scene (0–0.3: few; 0.3–0.6: median; 0.6–1: many). (III) Are there some obvious mistakes breaking the common sense in practice (0–0.3: many; 0.3–06: median; 0.6–1: few)
2	Historical	(IV) Contains historical conflicts (0–0.3: many; 0.3–06: median; 0.6–1: few) (V) Are there abnormal things exceeding the historical backgrounds, e.g new boats could not occur in that age (0–0.3: many; 0.3–06: median; 0.6–1: few).
2	Architectural	(VI) Contains architectural combination errors (0–0.3: many; 0.3–06: median; 0.6–1: few) (VII) Do the characteristics of architecture belong to the ancient Chinese near the Canal (0–0.3: completely not; 0.3–06: median; 0.6–1: totally yes);
2	Spacial-temporal Consistency	(VIII) Are there spacial-temporal conflicts, e.g. the wrong combination style or vegetation in current location (0–0.3: many; 0.3–06: median; 0.6–1: few) (IX) Are the styles of architectures and entities in the scene coherent (0–0.3: not; 0.3–06: median; 0.6–1: yes)
1	Other	(X) Is the same combination or component annotated consistently (0–0.3: completely not; 0.3–06: median; 0.6–1: totally yes)

Algorithm 2. The C_k in Algorithm 2 is the ontology of conflict sub-component w_k.

Algorithm 1: Onto-draw Generation Algorithm for Jing-Hang Grand Canal.

Data: Jing-Hang Grand Canal Ontology concept domain C, related ontology domains $C_1, C_2, \ldots C_n$, threshold θ, *max_try*.
Result: a suitable virtual Jing-Hang Grand Canal scene w with respect to concept domain C and consistent with C_1, C_2, … C_n.
begin
$incons \leftarrow 0, incons\_norm \leftarrow 0, exe\_count \leftarrow 0$
$w = F_\rho(V),\ \rho \subseteq R$ in $C(D, W, R, V)$
do
$w = adjustment(w, incons, incons\_norm)$
$exe\_count{+}{+}$
for each ontology C_i in $C_1, C_2, \ldots, C_n$
  $\forall v = Part - of(w)_{C_i}$
  if v is inconsistent with C_i
    if inconsistency occur in *normal* tags
      $incons\_norm{+}{+}$
    else $incons{+}{+}$
    end if
  end if
end for
if $maxe\_try \leqslant exe\_count$
  break
end if
while $incons \leqslant \theta$ & & $incons\_norm = 0$
return w
end

Algorithm 2: $adjustment(w, incons, incons\_norm)$

Data: Scene instance w, count *incons* and *incons_norm*.
Result: New scene w after regenerating the inconsistent sub-components.
begin
if $incons = 0 \&\& incons\_norm = 0$
  return w
else
  for each conflict sub-components w_k in w
    $w_k = F_\rho(V_k),\ \rho \subseteq R_k$ in $C_i(D_k, W_k, R_k, V_k)$
  end for
end if
return w
end

Table 2
Results of user study 1.

Input set	Average score	Standard deviation
$I_1 = H \cup R \cup A \cup N$	8.95	1.15
$I_2 = H \cup A \cup N$	5.56	2.38
$I_3 = H \cup R \cup N$	2.31	1.43
$I_4 = A \cup R \cup N$	4.23	1.77

Table 3
Results of user study 2.

Draw set	Average score	Standard deviation
O	6.88	1.57
M	5.61	2.11

6. Evaluation

6.1. User study to evaluate the draws

To further evaluate the effectiveness of our approach, we invited 40 Chinese native graduate students from different backgrounds to evaluate the results generated by our onto-draw engine with different ontology input. All of whom have visited the Jing-Hang Grand Canal in Hangzhou, but none of whom had previous experience doing 3D modeling of ancient Jing-Hang Grand Canal. Each participator spent twenty minutes following a tutorial of the historical and architectural backgrounds of the Canal in the Sui Dynasty, ten minutes for reading some literature about the scenes in that age, and seeing some illustrations[10] about the architectures and scenes; and another ten minutes for training by the historians and architects in our team, who try to teach them some basic professional knowledge about scenes of the Canal.

In our Grand Canal project, we totally used 513 characteristics in all the ontologies, among them, there are 133 items which are tagged with historical characteristics, noted as H; 44 items are tagged with regional characteristics, noted as R; 117 items are tagged with architectural characteristics, noted as A; 219 items are tagged with normal characteristics, noted as N;

Then we use four input sets, which is $I_1 = H \cup R \cup A \cup N$, $I_2 = H \cup A \cup N$, $I_3 = H \cup R \cup N$, $I_4 = A \cup R \cup N$, to generate four categories of draws via Algorithm 1, and each category generates five draws.

[10] They include draws from ancient literatures and some famous paintings in that age.

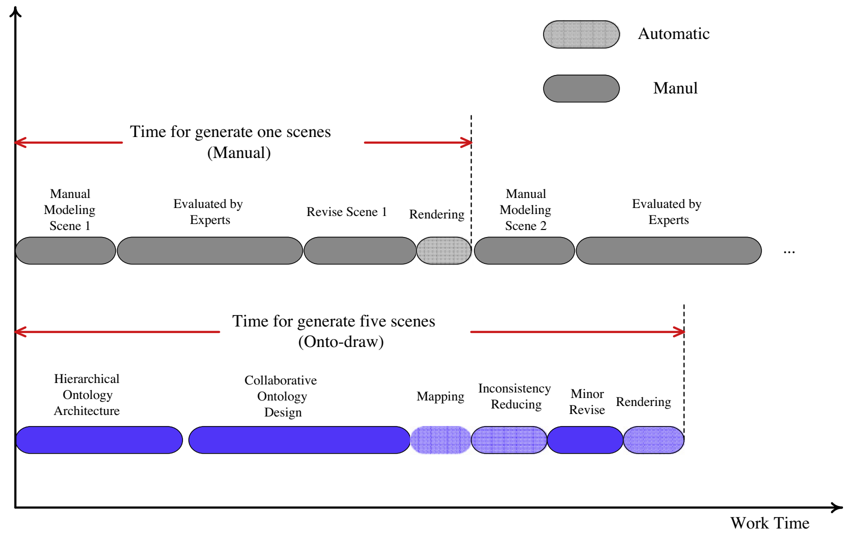

Fig. 7. A sample temporal comparison between our onto-draw and manual approach to model five sub scenes.

In our user study, the 20 draws are randomly presented to the testers and the participators grade the quality of the draws using the following scores: 0 for totally wrong, 5 for moderate between wrong and right, 10 for perfect, the value between 0 and 5 for less correct and the value between 5 and 10 for more correct. And the detailed score criteria are given in Table 1.

We record the scores of each draw by categories and then calculate the average scores for each category, the results are shown in Table 2. The average score for I_1 is 8.95, which suggests the onto-draw engine with all the descriptions could generate the Jing-Hang Grand Canal draws with high satisfaction. While the other three sets obtain obviously low scores, this suggests that the regional characteristics, architectural characteristics and historical characteristics are quite necessary in the onto-draw processing for Jing-Hang Grand Canal. Considering the scores of I_2, I_3, and I_4, the score of I_3 is much lower than the other two, which suggests the architectural characteristics may be the most crucial among I_1, I_2, I_3, corresponding with the validness of canal draws,[11] and the score of I_2 is almost over the medium degree, which suggests the regional characteristics may not be so noticeable as the regional diversity is easy to be ignored by the participators.

To evaluate whether the small sample size in our user study will introduce bias, we also calculate the standard deviation of the score for each category using the following formula:

$$\sigma_k = \sqrt{\frac{\sum_{i=1}^{n}\sum_{j=1}^{m}(x_{ij} - \bar{x}_k)^2}{n(m-1)}}$$

where x_k is the average score of category k, x_{ij} is the score assigned by participator i for the jth draw in category k, n is the number of participators and m is the number of draws in category k.

The standard deviation for each category is shown in Table 2. We also replace the scores with random values from the same distribution that resulted in a standard deviation of 3.281 on average, which is much larger than our results in four categories and proves that the sample for the user study is valid.

We also carried out another user study, which was tested by experts on the ancient Jing-Hang Grand Canal. In this test, we invited 16 experts, all of whom were familiar with the ancient Jing-Hang Grand Canal, either the historical backgrounds or the architecture styles, but none of whom had previously taken part in our onto-draw project. The second test employed two sets of scenes, O and M, O includes five draws generated by our onto-draw system, and M includes another five draws modeling manually by consulting with the same experts who designed the onto-draw. The process of the test is similar to the first user study, and using the same criteria (Table 1), the results are given in Table 3. The results show that the draws generated by onto-draw can achieve better average scores than the manual ones, which indicates that our onto-draw approach may be superior to the manual approach. Comparing the average scores of Tables 2 and 3, it also implicates indirectly that the experts may be more rigorous when commenting on the scenes.

6.2. Cost comparison between onto-draw and manual approach

As those complex models in the scenes are normally constructed manually, we carry out an experiment to compare the workload between the onto-draw approach and the manual modeling approach. Both approaches in the experiment try to generate five scenes of the urban near the Grand Canal, and we record the temporal cost of each approach, the results are shown in Fig. 7. In the manual approach, the scenes are generated one by one, each scene is first modeled by the experts of 3D model designers, then the historians and architects will evaluate the models and return to the designers for revising.

Although the workload of manual hierarchical ontology architecture design and collaborative ontology design in onto-draw approach is more than the manual modeling and experts' evaluation in the manual approach, the total workload of onto-draw is significantly less than the manual approach,[12] and there are more automatical processes in our onto-draw approach, which may be more suitable for the modeling of large scale scenes.

7. Results and analysis

Given limited space, we only show a small set of results here.[13] Fig. 8 shows six scenes of the virtual Jing-Hang Grand Canal with two typical styles: traditional Chinese painting style, Fig. 8(a), (b) and 3D rending style, Fig. 8(c)–(f). This figure shows highly detailed and

[11] Here we do not include the items tagged with *normal characteristics*.

[12] The workload of manual approach may be varied based on the skill of designers and domain experts.

[13] More results and demos please refer to http://www.nlict.zju.edu.cn/presentation/index.htm, http://www.nlict.zju.edu.cn/presentation/display.wmv, http://www.nlict.zju.edu.cn/presentation/out_gai_02-2.wmv.

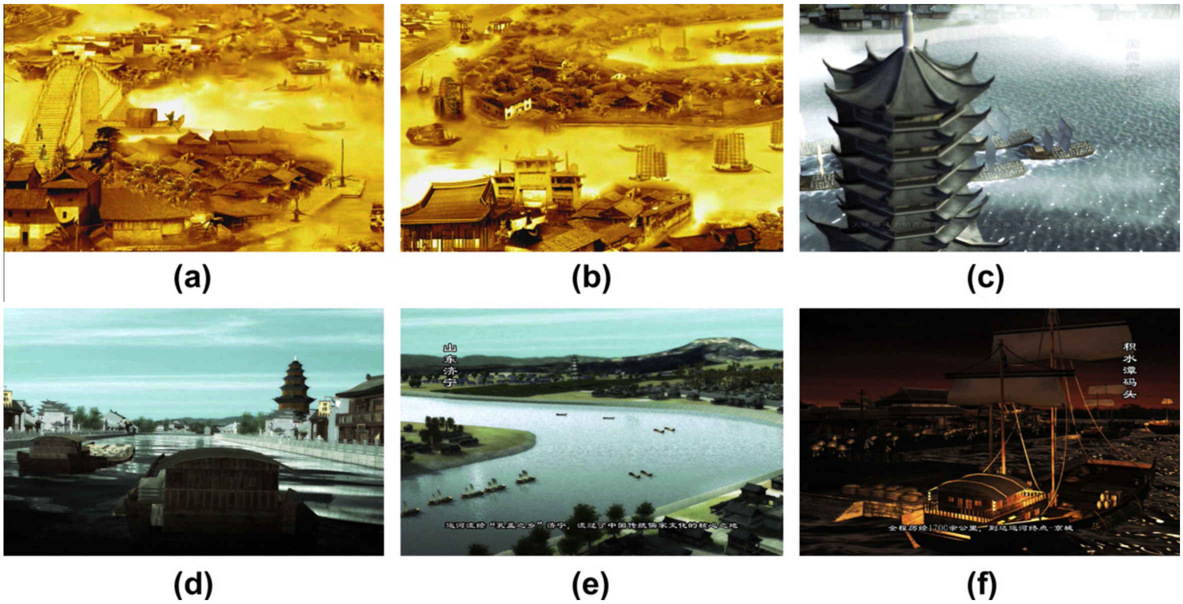

Fig. 8. Experimental results generated by the *Onto-draw* engine. (a), (b) are two scenes rendered with traditional Chinese painting style, (c), (d), (e), (f) are four scenes constructed by the *Onto-draw* rended with 3D style.

realistic scenes along the Jing-Hang Grand Canal. For example many porters carry goods into the boats by the riverside, and then boatmen ferry the goods along the river. There are also some other locomotive objects in the river or by the riverside, such as carriages, mill wheels, pedestrians and other workers as shown in Fig. 8(b) and (f). Fig. 8(a) also shows daily life scenes of the town near the Jing-Hang Grand Canal, ancient residents walking through the stone arch bridge and small boats navigating under the bridge. Fig. 8(c)–(f) exhibit the most important task of the Jing-Hang Grand Canal, official cargoes transferring from Hangzhou to Beijing, passing through half of China.

The advantages of using onto-draw to build the complex scenes such as Jing-Hang Grand Canal are summarized as follows.

- The onto-draw is a novel approach for solving the ontology concerning with spacial topology, which is different from those multimedia (most video) semantic annotation applications, e.g. M3O (Saathoff & Scherp, 2010), video (Bocconi et al., 2008). Instead of generating annotations for existing multimedia, onto-draw employs the structured knowledge from different domain experts, generates reasonable digital heritages with annotations automatically. To our knowledge, the onto-draw approach is the first solution for semantic digital heritages with spacial combination and topology based ontology.
- The design of ontologies in onto-draw is implemented based on the modular strategy, starting from small ontologies to combine them into a bigger one (bottom-up approach). Then complicated hard problems can be solved by solving some simple sub-problems. In practice, complex ontologies which contain multiple hierarchical elements are difficult to build. The onto-draw approach supports decomposing a complex ontology into several simple hierarchical ontologies and then removing their inconsistencies to synthesize the target complex ontology. Designing several simple ontologies is much easier than designing the complete and complex ontology.
- In our framework, the complex ontology is decomposed into many simple easy sub-domains, this makes it more scalable and easy to apply to solve other similar complex problems. As the onto-draw engine reduces the inconsistencies by processing the sub-ontologies incrementally, it can be easily applied in other similar concept domains by reusing the knowledge (Liu et al., 2008) and combining different sub-domains.
- With the onto-draw generation algorithm (Algorithm 1), the onto-draw engine can combine different ontology domains efficiently via the inconsistency detection. And it also provides a flexible method in processing the combination of ontologies.
- The onto-draw approach is especially suitable for designing complex concept domains in collaboration. The collaboration in onto-draw can optimize the design resources and minimize the labor cost in ontology design and integration. In practice, experts in different fields can independently input their own professional knowledge and concepts as ontologies without the need to consider knowledge from other experts. The onto-draw engine can automatically remove inconsistencies of different domains from different experts, finally, obtaining the desired solutions.

8. Conclusion

This paper proposes an onto-draw framework to design ontology for complex virtual scene modeling problem. The onto-draw approach, which has been implemented and successfully applied to the virtual Jing-Hang Grand Canal construction problem, can also detect and reduce the inconsistency between the modeling results and different ontology concept domains for other tasks.

There are a number of future directions for this work that will allow the system to be applied more broadly. They include: (1) developing automatic ontology concept matching method for the potential mapping relationship, (2) studying the condition of ontology evolvement in inconsistency detection, (3) optimizing the ontology design via machine learning techniques.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.eswa.2012.04.026.

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