A Semantic Tree-Based Approach for Sketch-Based 3D Model Retrieval

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***Abstract*—Sketch-based 3D model retrieval is to retrieve 3D models given a user's hand-drawn sketch. Due to the big semantic gap between rough sketch representation and accurate 3D model coordinates, sketch-based 3D model retrieval (SBR) is one of the most challenging research topics in the field of 3D model retrieval. To bridge the semantic gap, a novel semantic tree-based SBR algorithm is proposed in this paper. Given a 2D sketch query and a collection of 3D models, a 3D semantic tree is built up first based on the ontology structure of WordNet. Every leaf node in the tree contains a set of 3D models assigned to this class according to their semantic classification/label information. Then, sketch components of the 2D query sketch are identified by sketch segmentation and annotation. Finally, by measuring the semantic relatedness between the sketch components' annotations and tree nodes in the 3D semantic tree, the similarities between the 2D sketch and 3D models are computed to find out the most relevant 3D models. Experimental results demonstrate the effectiveness and promising potentials of our approach on sketch-based 3D model retrieval.**

I. Introduction

Sketch-based 3D model retrieval is to retrieve 3D models based on a query sketch. It plays an important role in many applications including sketch-based rapid prototyping, recognition, mobile 3D search, 3D printing, and 3D animation production etc. Existing sketch-based 3D model retrieval systems are mainly based on a direct content-based comparison between a 2D sketch query and sample views of all target 3D models. However, there is a big semantic gap between the iconic representation of 2D sketches and the accurate 3D coordinate representation of 3D models. This makes sketch-based 3D model retrieval become the most challenging research problem in the field of 3D model retrieval, which has been demonstrated by their low performance on several latest benchmarks including the SHREC'13 Sketch Track Benchmark (SHREC13STB) [15] and the SHREC'14 Sketch Track Benchmark (SHREC14STB) [18].

Motivated by the above obstacle, an interesting question is raised: "Can we use semantic information?" Semantic information describes high-level representation of both sketches and 3D models and therefore provides a bridge to reduce the gap between them. However, how to semantically compare 2D sketches and 3D models becomes a new research problem (Which semantic information should be considered? How can we extract it? How can we measure the similarity between the semantic information?). In the paper, we study these problems and propose a novel semantic tree-based 3D model retrieval algorithm.

Given a 2D query sketch and a dataset of 3D models, we first build up a 3D semantic tree in two steps. **Step 1:** Build a semantic tree based on the semantic ontology in WordNet [21]. WordNet is a lexical database of concepts/synsets, represented by a set of synonyms. Each node in the tree represents one word, which has one or more senses. Each sense has its synset and a set of words are related through the following three relationships: hypernyms/hyponyms (IS_A relation), holonyms (MEMBER_OF relation) and meronyms (PART_OF relation). **Step 2:** Classify the 3D models into certain nodes in the tree according to their semantic classification/label information (i.e. semantic concepts or names). Then, we identify the semantic attributes (i.e. semantic components) that the 2D query sketch contains by sketch segmentation and annotation. Finally, by measuring the semantic relatedness between the 2D sketch's components and the nodes in the semantic tree, we compute the similarities between the 2D sketch and 3D models to find out the most relevant 3D models.

To our best knowledge, this work is the first attempt to compare 2D sketches and 3D models at semantic level with a tree structure. The implication of this work could not only accelerate the research on sketch-based 3D model retrieval, but also shed inspiring light on human's sketch-related research work. Our main contributions introduced in this paper are highlighted as follows:

- A 3D semantic tree is created based on WordNet. It contains 407 3D models across 10 categories, which are located at different nodes in the tree.
- A novel semantic tree-based 3D model retrieval al-

gorithm is proposed. This approach can capture semantic information of 2D sketches effectively, measure similarities between semantics of 2D sketches and 3D models accurately, and therefore greatly enhance the retrieval performance.

- Comprehensive experiments have been conducted to compare the proposed approach and other state-of-the-art sketch-based 3D model retrieval methods. The experimental results demonstrate the effectiveness and potential of the proposed approach.
- Our work will explicitly guide the research on sketch-based 3D model retrieval and also provide a direction for sketch-based related applications.

II. Related work

In this section, we will review two prior related research directions: sketch-based 3D model retrieval, and WordNet-based semantic multimedia retrieval.

A. Sketch-Based 3D Model Retrieval

Given a 2D sketch query and a 3D model dataset, generally a sketch-based 3D model retrieval algorithm first samples a set of views for each 3D model, and then extracts a 2D shape descriptor to represent each view. Similarly, it extracts the 2D shape descriptor for the 2D sketch query. Next, it computes the minimum shape descriptor distances between the query sketch and all sample views and regards it as the sketch-model distance. Finally, it ranks all the target 3D models by sorting all the sketch-model distances.

Li and Johan [13] proposed a sketch-based 3D model retrieval algorithm based on 2D sketch-3D model alignment by using the view context feature proposed in [11] and shape context-base 2D contour matching. The 2D sketch-3D model alignment process shortlists a list of candidate views of a 3D model from a number of (i.e. 81) sample views to align it to a 2D sketch. It has achieved the best performance in several Eurographics Shape Retrieval Contest (SHREC) tracks on the topic of sketch-based 3D model retrieval, such as SHREC'13 Sketch Track (SHREC13STB) [15] and the SHREC'14 Sketch Track [18]. Still based on shape context-based matching, Li et al. [17] further developed a sketch-based 3D model retrieval algorithm based on the idea of performing view clustering on the sample views of a 3D model to shortlist candidate views for the purpose of sketch-model matching.

Recently, substantial research work has been performed in sketch-based 3D model retrieval. For instance, the Histogram of Gradient (HOG) feature has been used in [31], followed by the Overlapped Pyramid of HOG (OPHOG) feature by Tatsuma and Aono [16]. Later, Eitz et al. [5] proposed the Gabor local line-based feature (GALIF), while Li et al. [14] developed a parallel shape context-based matching algorithm for the retrieval.

Four Shape Retrieval Contest (SHREC) [1], [15], [18], [19] tracks on the topic of sketch-based 3D model retrieval have been held in conjunction with the 2012, 2013, 2014 and 2016 Eurographics Workshops on 3D Object Retrieval (3DOR). In each track, different methods have been evaluated on the corresponding benchmarks, for example, the SHREC'13 Sketch Track Benchmark (SHREC13STB) [15], which contains 7200 2D sketches and 1258 3D models of 90 classes, and the SHREC'14 Sketch Track Benchmark (SHREC14STB) [18], which contains 13680 2D sketches and 8987 3D models of 171 classes.

Huang et al. [8] proposed a data-driven 2D sketch segmentation and labeling algorithm, which can effectively and efficiently segment and label sketches of commonly used objects. They built a ground-truth dataset which contains labeled component information for 300 sketches of 10 classes (each with 30 sketches): chair, table, airplane, bicycle, fourleg, lamp, vase, human, candelabrum, and rifle. To the best of our knowledge, it achieves a state-of-the-art overall labeling accuracy, which is 66.7%.

B. WordNet-Based Semantic Multimedia Retrieval

As a lexical dictionary of semantic concepts, WordNet has been vastly applied in semantic multimedia retrieval of either text or image objects. Aslandogan et al. [2] utilized WordNet for query and database expansion in image retrieval. Database expansion refers to expanding the metadata in the database. They considered synonyms of nouns and verbs, different number of (first or all) senses of a word, and other three relationships (IS_A, MEMBER_OF, and PART_OF) mentioned before. They found that for query expansion the optimal setting is using synonyms of all senses, or considering the synonyms and the IS_A and MEMBER_OF relations of the first sense of a word.

Marszalek and Schmid [20] proposed to utilize WordNet to build a semantic and hierarchical graph for the objects involved. Based on labeled training data, they learned a binary classifier for each node in the graph. Wang et al. [29] proposed to build an ontology based on WordNet for a 3D model benchmark, infer 3D semantic properties by rule engine based on Semantic Web Rule Language (SWRL), and perform semantic retrieval using the ontology.

A survey on three typical semantics processing (relevance feedback, machine learning, and ontology) has been performed in [6], while Tousch et al. [28] presented a survey on semantics-based image annotation.

WordNet-Based Semantic Distance Metrics. To measure the relatedness of two semantics in WordNet, several semantic similarity and relatedness metrics have been proposed. For example, Pedersen et al. [26] implemented three similarity measures that are based on path lengths between concepts: *lch* [9], *wup* [30], and *path*; and three semantic relatedness measures: *hso* [7], *lesk* [4], and *vector* [22]. Other semantic relatedness and similarities have been proposed in [23] and [25], as well.

WordNet-Based Sense Disambiguation. When we look up a word from WordNet, it usually lists several senses of the word to indicate the different meanings that the word may have in different text contexts. Therefore, deciding which sense should be adopted for a situation, that is word sense disambiguation, is very important for

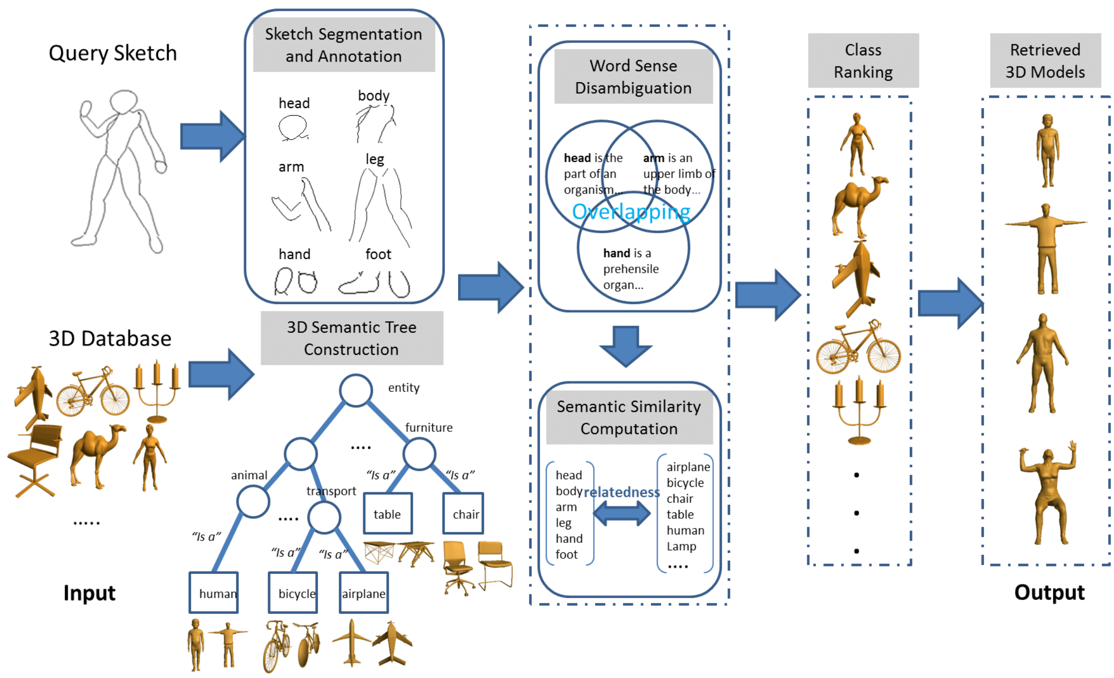

Fig. 1. Framework of our semantic tree-based SBR algorithm.

its correct interpretation. Different approaches have been proposed for word sense disambiguation. For example, for such purpose, Banerjee and Pedersen [3] proposed using an adapted Lesk algorithm for word sense disambiguation. The main idea of the original Lesk algorithm [10] is based on the following two hypotheses: a word in a sentence can be disambiguated by its neighboring words by assigning the most closely related sense to it; and overlapping words in the glosses of neighboring words are helpful to identify their related senses. Therefore, they conducted sense disambiguation by comparing the number of overlapping words between the gloss of a word and the glosses of its neighboring words. Pedersen et al. also developed several software for sense disambiguation, such as WordNet::SenseRelate::WordToSet [24], which is specially designed for the sense disambiguation problem for one word per a set of related words.

III. Algorithm

In this paper, a semantic tree-based SBR algorithm is proposed to retrieve relevant 3D models similar to a 2D sketch query. The framework of our approach is illustrated in Fig. 1. The details of every module are described as follows.

1) **Input.** Users draw a 2D sketch as an input. The retrieval algorithm is to find relevant 3D models to the query in the given 3D model database.

2) **2D Sketch Segmentation and Annotation.** 2D sketch segmentation is to partition a query 2D sketch q into a set of consistent semantic components $\{C_i\}$. For the i-th component C_i, we assign a semantic name as a component attribute A_i^q of the query sketch q according to the PART_OF relationship. After this step, each component has a semantic label. For example, a human sketch can be segmented and labeled into the following parts: foot, hand, leg, arm, body, and head, as shown in Fig.1. Some part labels may appear more than once, such as the foot, leg and arm labels in this example. Considering the best performance, for this step, we employ the 2D sketch segmentation and labeling algorithm proposed in [8].

3) **Semantic Tree Construction.** Given a 3D model database, a 3D semantic tree, as shown in Fig. 1, is built up, which is a hierarchy of classes (*nouns*) based on the semantic hierarchy in WordNet. Each class has several attributes (i.e. is-a, has-part, or is-made-of relations) according to its gloss defined in WordNet. Each leaf node of the 3D semantic tree has a number of 3D models belonging to the leaf node class. Therefore, the 3D semantic tree forms a network of classes, attributes and models: a) **Classes**: The 3D models in the target 3D model dataset are classified into a number of classes, which correspond to the leaf nodes, denoted as $\mathbf{N}$=$\{N_i\}$, in the WordNet-based hierarchical tree; b) **Attributes**: Each leaf node N_i possibly has several semantic attributes (i.e. semantic components) according to its definition (gloss), denoted as $\{A_{ij}\}$; c) **3D models**: We assume that all the existing target 3D models can be pre-classified into a set of leaf nodes (classes) according to their available/learned label information, while new models can be dynamically and automatically classified and inserted into the 3D semantic tree. One such example is ShapeNet [27].

4) **Word Sense Disambiguation.** To compute the semantic relatedness value between a labeled semantic component of the 2D sketch query and the name of a 3D model category, we need to decide which sense (meaning) that the label name should take. Motivated by the two hypotheses of the Lesk algorithm, for each component's label, we regard other components' labels as its context.

Then, we perform its sense disambiguation by counting the number of overlapping words between the gloss of the component's label and the glosses of other components' labels. Considering the fact that any two components of a sketch, though logically related, are often semantically different (thus using similarity metrics is inappropriate), we choose the Lesk relatedness metric to measure their similarities.

5) **Semantic Similarity Computation.** Semantic similarity computation is to compute the sketch-model similarity $S(q, N_i)$ based on the component-wise relatedness $R(A_i^q, N_i)$ between a component attribute A_i^q of the query sketch q and a semantic class N_i. Thanks to the WordNet gloss and semantic hierarchy in the 3D semantic tree, the relatedness between a set of sketch segments' names and the gloss of a model's class name can be easily measured by using the algorithm *hso* [7] and *lesk* [4]. We find that *hso* performs the best in our experiments.

Moreover, the complexity of sketches may be an important factor in deciding the query-sketch semantic similarity. While, the sketch complexity can be measured based on the number of components in the sketch. In order to explore how much the consideration of sketch complexity will affect the semantic similarity measurement, we have developed three relatedness fusion methods: Average, Sum and Product. These three methods treat sketch complexity differently in measuring the semantic similarity. The Average method divides the total sum of component-wise relatedness values by the total number of components n in the sketch query. The Average method doesn't consider sketch complexity in distance measurement. The Sum method directly adds all component-wise relatedness values together in order to integrate the sketch's complexity into the semantic similarity. The Product approach further multiplies the value computed in the Sum method by n in order to assign a bigger weight for more complicated sketches. Based on our experiments, the Product approach performs the best.

6)**Ranking and output.** Sort query-class similarity $S(q, N_i)$ in a descending order and then list all the models in respective classes accordingly.

IV. Experiments and Discussions

A. Benchmark

2D sketch dataset: We randomly selected sketches from the 300 sketches dataset collected in [8] as queries for our retrieval algorithm. These sketches are equally classified into 10 classes: chair, table, airplane, bicycle, fourleg, lamp, vase, human, candelabrum, and rifle. Ten query sketch examples are shown in Fig. 2.

3D model dataset: We collected 407 models in total for the same 10 classes: airplane (70 models), bicycle (38 models), candelabrum (28 models), chair (70 models), quadruped (20 models), human (20 models), lamp (20 models), rifle (19 models), table (61 models), and vase (61 models). Fig. 3 shows one example for each class.

Evaluation metrics: To conduct a comprehensive and comparative evaluation between our semantic tree-based 3D model retrieval algorithm and other traditional content-based 3D model approaches on the above benchmark, we adopt seven commonly used performance metrics [12] in the information retrieval area: Precision-Recall (PR) diagram, Nearest Neighbor (NN), First Tier (FT), Second Tier (ST), E-Measures (E), Discounted Cumulated Gain (DCG), and Average Precision (AP).

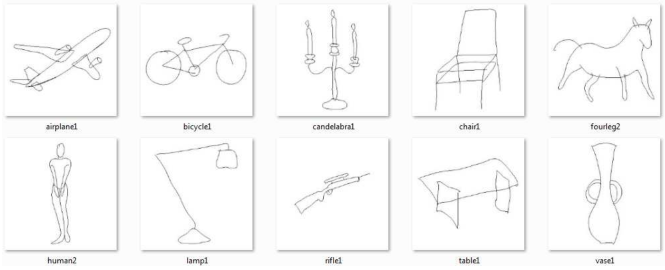

Fig. 2. Example 2D sketch queries.

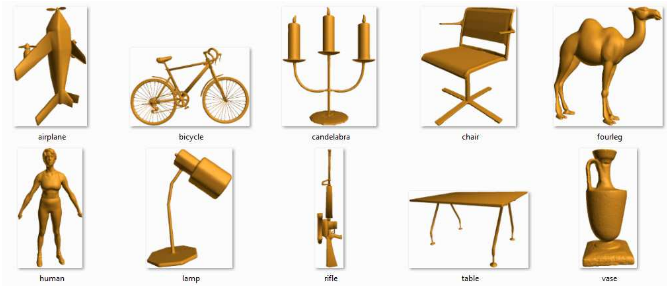

Fig. 3. Example 3D models.

B. Experimental Results and Discussions

Steps 1 & 2: 2D sketch segmentation and annotation. To find out the best performance that can be achieved for our semantic approacch, we perform sketch segmentation on the query sketch and annotate the sketch components with the ground-truth segment labels in the sketch dataset [8]. As mentioned, currently the state-of-the-art accuracy [8] is around 67% on the sketch dataset [8].

Step 3: Word sense disambiguation. The sense numbers in the latest WordNet v3.1 are used. Our manual (as a baseline) and automatic word sense disambiguation results for all the ten queries are shown in Fig. 4 and Fig. 5, which show that there is still much room for further improvement in this step.

Sketch	Component Senses
Airplane	engine 1 engine 1 stabilizer 2 stabilizer 2 stabilizer 2 wing 2 wing 2 body 5
Bicycle	frame 8 fork 3 chain 3 handle 1 wheel 1 wheel 1 frame 1 saddle 5
Candelabra	arm 2 arm 2 shaft 3 flame 2 flame 2 flame 2 candle 1 candle 1 candle 1 base 2
Chair	armrest 1 seat 4 stretcher 2 leg 3 leg 3 leg 3 leg 3 stile 1 stile 1 back 8 stretcher 1 stretcher 1 stretcher 1
Quadruped	tail 1 leg 2 leg 2 leg 2 leg 2 head 1 ear 1 ear 1 body 5
Human	foot 1 hand 1 hand 1 leg 1 leg 1 leg 1 leg 1 body 1 head 1 arm 1 arm 1 leg 1 leg 1 foot 1
Lamp	shade 3 base 2 tube 1 tube 1
Rifle	sights 1 butt 1 trigger 1 handgrip 1 body 5 barrel 1
Table	leg 3 leg 3 top 1
Vase	body 5 handle 1 handle 1 lip 4

Fig. 4. Manual word sense disambiguation for the component labels of the ten query sketches.

Sketch	Component Senses
Airplane	engine 3 engine 3 stabilizer 3 stabilizer 3 stabilizer 3 wing 1 wing 1 body 2
Bicycle	frame 8 fork 5 chain 8 handle 1 wheel 1 wheel 1 frame 8 saddle 1
Candelabra	arm 1 arm 1 shaft 3 fire 2 fire 2 fire 2 candle 2 candle 2 candle 2 base 9
Chair	armrest 1 seat 4 stretcher 4 leg 1 leg 1 leg 1 leg 1 stile 1 stile 1 back 5 stretcher 4 stretcher 4 stretcher 4
Quadruped	tail 1 leg 1 leg 1 leg 1 leg 1 head 1 ear 1 ear 1 body 1
Human	foot 1 hand 1 hand 1 leg 1 leg 1 leg 1 leg 1 body 1 head 1 arm 1 arm 1 leg 1 leg 1 foot 1
Lamp	shade 2 base 9 tube 1 tube 1
Rifle	sights 3 butt 9 trigger 1 handgrip 1 body 2 barrel 2
Table	leg 1 leg 1 top 9
Vase	body 2 handle 1 handle 1 lip 1

Fig. 5. Automatic word sense disambiguation for the component labels of the ten query sketches based on the Lesk relatedness metric.

Step 4: Semantic similarity computation. The *hso* [7] relatedness approach is adopted for its great performance.

Step 5: Ranking and output. Based on the query-class semantic similarity values, we rank the classes and the corresponding 3D models accordingly.

We designed a set of experiments to fully test and compare the following approaches on sketch-based 3D model retrieval: 1) our semantic tree-based SBR algorithm (TSBR) with different relatedness fusion methods (Product, Sum, and Average); 2) our semantic tree-based SBR algorithm with automatic word sense disambiguation for the query sketch component labels (TSBR-AWSD); 3) other traditional content-based 3D model retrieval approaches. Two shape context matching-based approaches SBR-VC and SBR-2D-3D perform the best on the SHREC'13 Sketch Track Benchmark [15]. They either shortlist four candidate views (SBR-2D-3D) or cluster a few representative views (SBR-VC) based on the same set of 81 sample views for each 3D model. Here, we implement a brute-force shape context-based matching algorithm denoted as SBR. SBR considers all the 81 sample views for each model and therefore outperforms both SBR-VC and SBR-2D-3D due to its completeness.

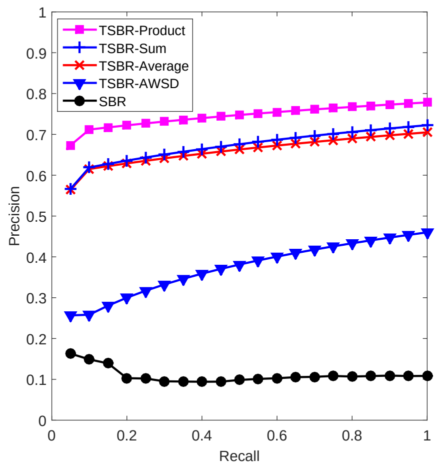

Fig. 6. Comparison of Precision-Recall plots of our approaches and SBR [15].

Fig. 6 and Table I show the comparison results in terms of the seven evaluation metrics. We find that our approach with the Product approach performs the best, consecutively followed by the Sum and Average approaches. We believe this is due to the enhancement effect in the differentiation ability of the Product approach after considering the 2D sketch complexity. As expected, automatic word sense disambiguation achieves 50%∼75% performance of manual word sense disambiguation. Most importantly, our approaches dramatically improve retrieval performance compared with traditional content-based 3D model retrieval methods (SBR). For a further validation, we also tested SBR on all the 300 sketches collected in [8] as well and found consistent (similar) SBR performance: NN: 0.07, FT: 0.08, ST: 0.17, E-Measure: 0.06, DCG: 0.47, AP: 0.11.

TABLE I. Comparison of six performance metrics of our approaches and SBR [15].

Benchmark	NN	FT	ST	E	DCG	AP
TSBR-Product	**0.70**	**0.70**	**0.79**	**0.51**	**0.84**	**0.75**
TSBR-Sum	0.60	0.60	0.76	0.45	0.79	0.67
TSBR-Average	0.60	0.60	0.69	0.45	0.79	0.66
TSBR-AWSD	0.20	0.32	0.50	0.24	0.59	0.37
SBR	0.20	0.07	0.14	0.06	0.46	0.11

31	8	0	12	4	5	10	0	12	0
15	**26**	0	4	3	4	0	6	3	0
14	5	0	0	0	0	0	2	0	0
29	25	0	**33**	0	0	12	14	31	0
0	0	0	0	**40**	**40**	0	0	0	0
0	0	0	0	40	**72**	0	0	0	0
8	**11**	0	2	0	0	6	8	0	0
3	15	0	0	4	5	0	**20**	0	0
6	6	0	**8**	0	0	4	4	**8**	0
2	12	0	0	4	5	0	8	0	**20**

Fig. 7. Query-class *hso* semantic similarity matrix for the 10 queries. Each row/column is for a query/class according to the order in Fig. 2/3.

Fig. 7 shows the query-class *hso* semantic similarity matrix of TSBR-Product for the 10 queries. It is observed that there are *non-trivial* differences in terms of the *hso* relatedness values for different classes, which helps us to separate different classes easily. Fig. 8 lists the ranked classes (one example per class) accordingly. These ranking results show that our approach can successfully find the most relevant classes given a query sketch.

In a word, these experimental results demonstrate that our semantic search approach has achieved outstanding results on 3D model retrieval, though currently only on a small benchmark. Our approach can capture semantic information of 2D sketches effectively, measure similarities between semantics of 2D sketches and 3D models accurately, and therefore largely enhance the retrieval performance.

V. Conclusions

In this paper, we propose a semantic tree-based approach to retrieve 3D models given a 2D sketch query. To measure the semantic similarity between a query 2D sketch and a 3D model, we utilize WordNet ontology to compute the semantic relatedness between the annotations of the sketch's components and a 3D model class. During the computation, we also perform word sense disambiguation to assign correct meaning for components' labels. Experiments have demonstrated the superior performance of our approach than the traditional content-based 3D model retrieval approaches.

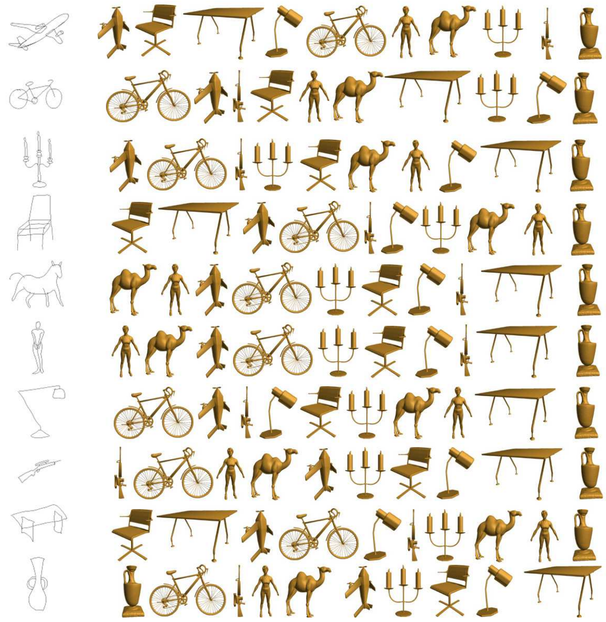

Fig. 8. Ranking classes for the 10 queries. One example for each of the 10 classes is displayed according to their ranking order.

Acknowledgments

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