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

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Overview

- **Research topic:** Sketch-Based 3D model retrieval (SBR)
  - Retrieve 3D models from a dataset given a user's hand-drawn sketch.
  - Applications: sketch-based rapid prototyping, mobile 3D search, 3D printing, and 3D animation etc.
- **Semantic gap**: Big semantic gap exists between traditional human-drawn 2D sketches and 3D models.
  - Rough sketch representation and accurate 3D model coordinates.
  - SBR is one of the most challenging research topics in the field of 3D model retrieval.
- **Semantic information:** Describes high-level representation of both sketches and 3D models.
  - Provides a bridge to reduce the semantic gap between them.
  - A novel **semantic tree-based SBR algorithm** is proposed to **bridge** the semantic gap.
- **Research results:** Experiments demonstrate the effectiveness and promising potentials of our approach.
- **Contributions**
  - **(1)** A **3D semantic tree** is created based on WordNet [1].
    - It contains 407 3D models across 10 categories and at different nodes in the tree.
  - **(2)** A novel **semantic tree-based 3D model retrieval algorithm** is proposed. This approach
    - Effectively captures semantic information of 2D sketches.
    - Accurately measures similarities between semantics of 2D sketches and 3D models.
    - Greatly enhances the retrieval performance.
  - **(3) Comprehensive comparative experiments** have been conducted to compare with other state-of-the-art methods.
    - Experiments demonstrate the effectiveness and potential of the proposed approach.
  - **(4) Our work** will
    - Explicitly **guide** the research on sketch-based 3D model retrieval.
    - Provide a direction for sketch-based related applications.

Algorithm

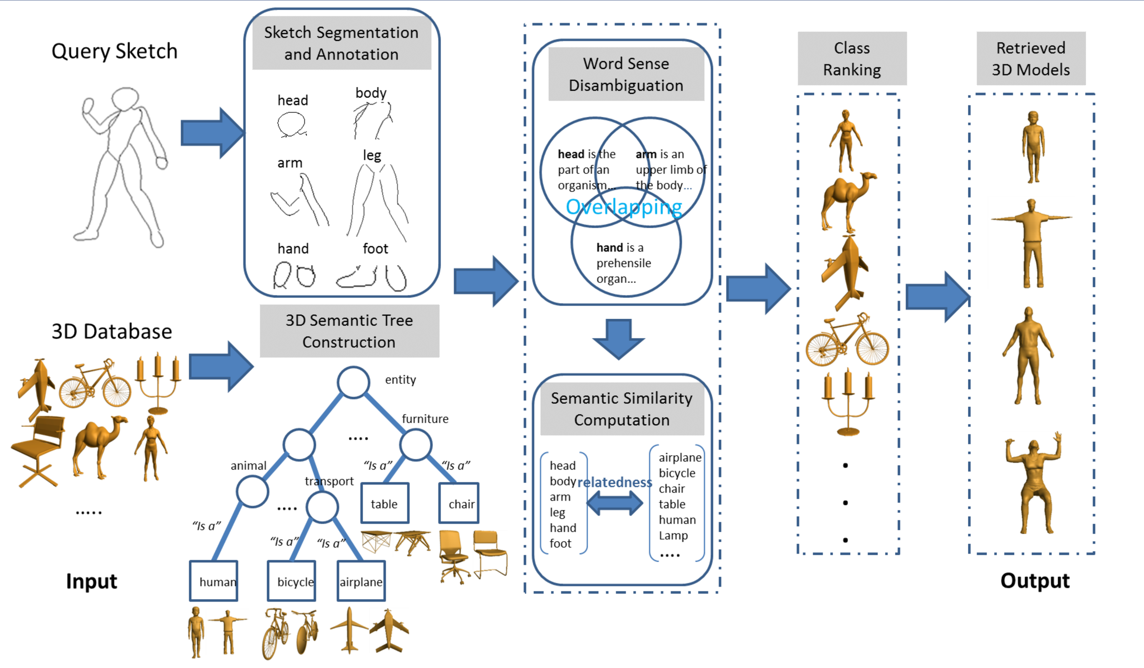

Fig. 1. Framework of our semantic tree-based SBR algorithm.

- **1) Input:**
  - A User-drawn 2D sketch.
  - A given 3D model database.
- **2) 2D Sketch Segmentation and Annotation:** Segments a sketch q into a set of consistent semantic components $\{C_i\}$, and then recognizes each component's category label q_i. One example is demonstrated in **Fig. 2**:

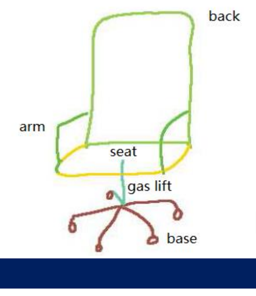

Fig. 2. Example Sketch Segmentation and Annotation [8]

Algorithm (Cont.)

- **3) Semantic Tree Construction:** Build a semantic tree based on the semantic ontology in **WordNet**, which is
  - A lexical database of concepts/synsets, represented by a set of synonyms.
  - Each word has one or more senses (meanings), each having its synset.
  - Words are related through *three relationships*: Hypernyms/hyponyms (**IS_A** relation), Holonyms (**MEMBER_OF** relation), and Meronyms (**PART_OF** relation).
- **4) Word Sense Disambiguation:** Decide which sense to take for a label name,
  - Either for a labeled semantic component of the 2D sketch query or the name of a 3D model category.
  - By counting the **number of overlapping words** between the gloss of the component's label and the glosses of other components' labels [5].
- **5) Sketch-Model Semantic Similarity Computation:** Compute the component-wise relatedness between each sketch component's category name and a semantic class in the semantic tree.
- **6) 3D Model Ranking**: Sort query and class similarities and rank the models in respective classes based on their shape similarities.

Experiments

- **Dataset collection**
  - **2D sketch dataset:**
    - Randomly selected sketches from the 300 sketches dataset collected in [2] as queries.
    - One query sketch for each class is shown in Fig. 3.
  - **3D model dataset:**
    - We collected 407 models in total for the same 10 classes.
    - One example 3D model for each class is shown in Fig. 4.

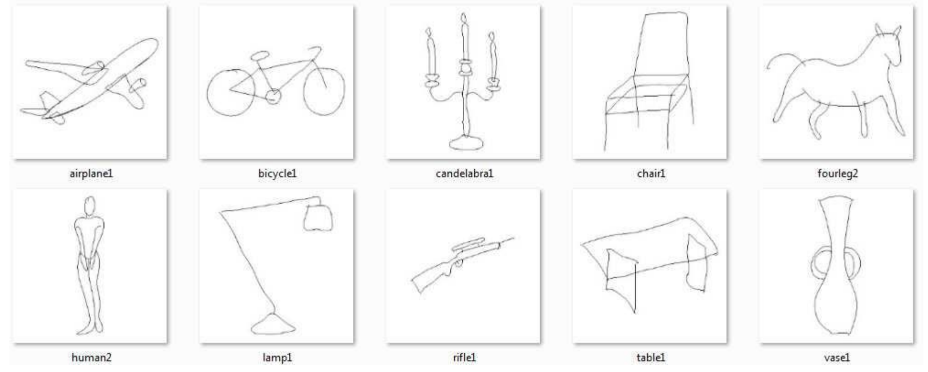

Fig. 3. Example 2D sketch queries.

Fig. 4. Example 3D models.

- **Evaluation metrics [3]:**
  - Precision-Recall (PR) diagram, Nearest Neighbor (NN), First Tier (FT), Second Tier (ST), E-Measures (E), Discounted Cumulated Gain (DCG), and Average Precision (AP).
- **Performance:**
  - Three different relatedness fusion methods: Product, Sum and Average.
  - Product approach performs the best.
  - Our approaches dramatically improve retrieval performance compared with traditional content-based SBR methods.

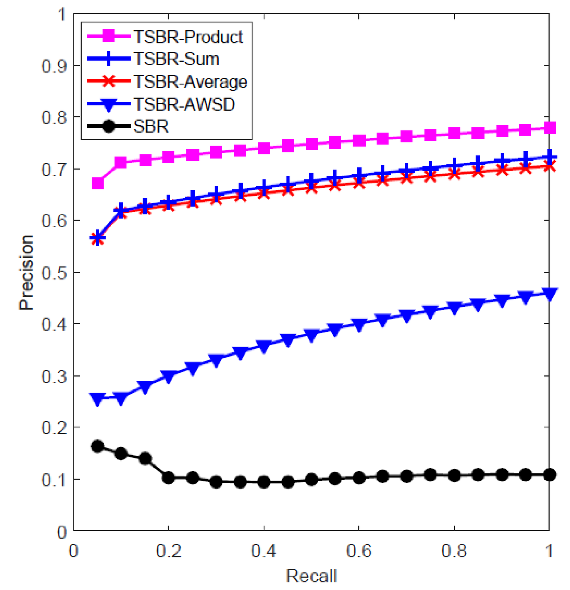

Fig. 5. Comparison of Precision-Recall plots of our approaches and SBR [4].

Table 1. Comparison of six performance metrics of our approaches and SBR [4]. **TSBR**: our semantic Tree-based SBR algorithm.

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

Experiments (Cont.)

- **Query-class *hso* semantic similarity matrix**
  - **Non-trivial** differences in *hso* relatedness values->good differentiability.

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. 6. Query-class *hso* semantic similarity matrix for the 10 queries. Each row/column is for a query/class according to the order in Fig. 3/4.

- **Ranking classes for the 10 queries.**
  - Classes are often logically ranked.

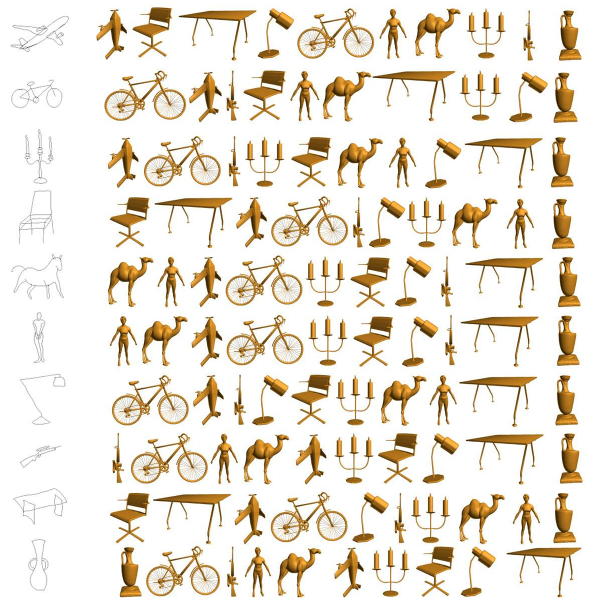

Fig. 7. Ranking classes for the 10 queries. One example for each of the 10 classes of 3D models is displayed according to their ranking order.

References

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