Overview

- **Research topic:** 3D Sketch-based 3D model retrieval (SBR)
  - Retrieve 3D models from a dataset given a user’s hand-drawn 3D sketch
  - Promising in game design, 3D animation and human-computer interaction, etc.
- **3D Sketching:** we collect sketches using Microsoft Kinect
  - Encodes 3D information, depth and features of more facets of the object
  - Includes the salient 3D feature lines of its counterpart 3D models

Challenges

- **Compliance:** 3D sketching is more complex than 2D sketching
  - Drawing a 3D horse is more difficult than drawing a 2D horse on a paper
  - Variation: one thousand people may draw the same object in one thousand different ways
  - Uncertainty: 3D sketches only record 3D coordinates of all the individual points captured from human’s hand movement during sketching
  - A lot of noisy and inaccurate points are captured due to hand shaking, object occlusion, and camera delay
- **Research results:** The experimental results reveal our approach outperforms other state-of-the-art and demonstrates promising potentials of our approach on 3D sketch-based application.
- **Contributions:**
  - A novel 3D sketch-based 3D model retrieval system is introduced to solve the matching problem between 3D sketches and 3D models
  - Our SBR-system combines multiple machine learning and 3D vision processing techniques, which will explicitly guide the research in 3D sketch understanding
  - Comprehensive experiments have been conducted to evaluate the state-of-the-art sketch based retrieval approaches on 3D sketch-based 3D model retrieval
  - The experimental results not only show our approach outperforms other state-of-the-arts, but also demonstrates promising application potential of our approach on 3D sketch understanding, on-line 3D model shopping, and large scale 3D model search, etc.

Algorithm

- **Input:** Original 3D sketch dataset S
  - Output: Extracted 3D sketch dataset D with random rotations, and flips
    - Initiation:
      \[ w = \text{width}_{\text{sketch}} - \text{width}_{\text{Template}} \]
    - for \( i = 1 \) to \( 300 \) do
      - \( C = \text{topk}(C) \)
      - \( x_{\text{sketch}} \sim \text{random}(0, w) \)
      - \( x_{\text{Template}} \sim \text{random}(0, l) \)
      - \( C = C \oplus \{ \text{box}(x_{\text{sketch}}, x_{\text{Template}}, w) \} \)
      - \( \text{red} = \text{random}(0, l) \)
      - if \( \text{red} < 0.5 \) then
        - \( \text{red} \sim \text{random}(-0.5, 0.5) \)
      - \( C = \text{rotate}(C, \text{red}) \)
      - \( \text{replicate}(T, C) \)
    - end
- **Data processing:**
  - To adapt the framework for 2D sketch-based CNN model, we need to convert the 3D sketches to 2D sketch views
  - Project all the coordinates in each 3D sketch to its six square faces if we regard a 3D sketch as regular hexahedron
  - Map the 3D coordinates to 2D depth image
  - Convert both TU Berlin dataset and 2D sketch views by 500 times using random rotation, shift and flip (see Algorithm 1)
- **Majority vote and label matching:**
  - Rescale the similarities between a 3D sketch and target 3D model categories to range [0, 1]. A higher value means bigger similarity
  - Count the number of top-1 labels among six similarity vectors for each target 3D model category
  - Compute the average similarity between this sketch and target 3D model categories based on six similarity vectors
  - Rank all the target 3D model categories using the summation of the top-1 label count and the average similarity
  - Rank all the related models accordingly

Experiments

- **To comprehensively evaluate the performance of our CNN-SBR system, we participated in 2016 Shape Retrieval Contest (SHREC'16), which targets on 3D sketch-based 3D model retrieval**
  - **SHREC'16 3D Sketch Track Benchmark** for learning based participating algorithms and on the complete dataset for non-learning based algorithms
  - **SBR system**, we participated in 2016 Shape Retrieval Contest (SHREC'16) track which targets on 3D sketch-based 3D model retrieval
  - We collect 3D sketches using Microsoft Kinect and demonstrate promising potentials of our approach on 3D sketch based application.

Algorithm (Cont.)

Input: Original 3D sketch dataset S
Output: Extracted 3D sketch dataset D with random rotations, and flips
Initiation:
\[ w = \text{width}_{\text{sketch}} - \text{width}_{\text{Template}} \]
for \( i = 1 \) to \( 300 \) do
  - \( C = \text{topk}(C) \)
  - \( x_{\text{sketch}} \sim \text{random}(0, w) \)
  - \( x_{\text{Template}} \sim \text{random}(0, l) \)
  - \( C = C \oplus \{ \text{box}(x_{\text{sketch}}, x_{\text{Template}}, w) \} \)
  - \( \text{red} = \text{random}(0, l) \)
  - if \( \text{red} < 0.5 \) then
    - \( \text{red} \sim \text{random}(-0.5, 0.5) \)
  - \( C = \text{rotate}(C, \text{red}) \)
  - \( \text{replicate}(T, C) \)
end
Algorithm 1: Data augmentation algorithm

References


Acknowledgment

This work is supported by Army Research Office grant W911NF-12-1-0057, NSF CNS-1305302 and NSF CNS-1358939 to Dr. Lu.