

# Component Segmentation of Sketches Used in 3D Model Retrieval

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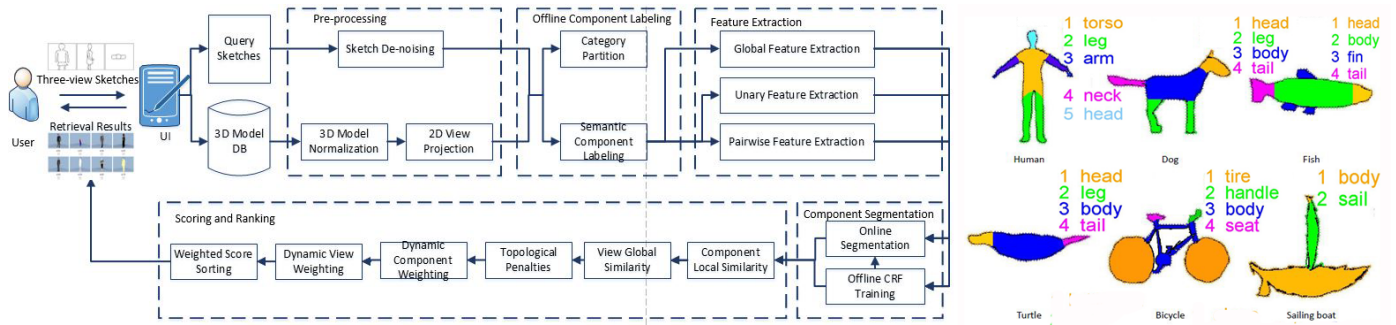


Figure 1: Left: Overall retrieval architecture of our method; Right: Segmentation results by using CRF

## 1 Introduction

Sketching is a natural human practice. With the popularity of multi-touch tablets and styluses, sketching has become a more popular means of human-computer interaction. However, accurately recognizing sketches is rather challenging, especially when they are drawn by non-professionals. Therefore, automatic sketch understanding has attracted much research attention. To tackle the problem, we propose to segment sketch drawings before analyzing the semantic meanings of sketches for the purpose of developing a sketch-based 3D model retrieval system.

At the offline stage of the new method, we first project each 3D model in a database to obtain its projection images. We then evenly sample contours in the projection images to obtain sequences of contour points. We manually tag a component label on each sample point to develop a dataset for component segmentation. Then, we extract unary features and pairwise features. Finally, we utilize JointBoost classifier and Conditional Random Field (CRF) to perform segmentation. At the final step of off-line procedure, we extract the bag of Gabor feature as local features for each component. In addition, for each projection image, low-rank Zernike moments are formulated as global features to take overall information into consideration. At the on-line stage, given a set of query sketches, we segment them into semantic components based on learned CRF models. We evaluate the similarity between sketch components and the corresponding components of projection contours. The final ranking score between sketches and a model is calculated according to three terms extracted from three views, namely the weighted summation of component similarity, topological dissimilarity penalties, and similarity between sketch and projection image. We also propose a dynamic weighting strategy, which automatically weights each component and each viewpoint. We conduct experiments and validate retrieval results with Princeton Shape

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Benchmark (PSB). Based on the comparison and analysis of the experimental results, we illustrate the feasibility and validity of our method.

## 2 Our Approach

The core module of our retrieval system is a data-driven segmentation algorithm for labeling semantic components of sketches. We found that simplified polygon obtained from Discrete Curve Evolution (DCE) provides useful information for semantic component segmentation because pre-segmentation facilitates collecting and labeling training dataset. For each sample point, we use six unary features, including: Shape Context Histogram, Average Euclidean Distance, 2D Shape Diameter, distance to the image center, ratio of connected component and relative tangent angle. The absolute values of shape diameter difference and tangent angle difference are used as pairwise features.

Predicting the label of component can be considered as an optimization process of CRF [Kalogerakis et al. 2010]. The objective function of CRF is formulated by unary terms, which measure the consistency between features and labels, and pairwise terms, which evaluate the compatibility between labels of neighbor points. The basic probability distributions in unary and pairwise terms are estimated by JointBoost classifiers. Cross validation technique and Graph Cut optimizer are used to learn the remaining parameters of CRF.

Our new method assumes that understanding semantically-coherent components in sketch drawings are easier to perform than dealing with an entire sketch drawing. Component-level regional information not only benefits feature selection but also empowers the discriminability of the selected features for sketch understanding. At present, the method only considers contours in projected views during sketch-based model retrieval. In the future work, we plan to specially examine stylistic and artistic strokes and components in a sketch drawing to generalize the applicability of the proposed method for more accurately and reliability understanding meanings of sketch drawings for sketch-based 3D model retrieval.

## References

KALOGERAKIS, E., HERTZMANN, A., AND SINGH, K. 2010. Learning 3d mesh segmentation and labeling. In *ACM Transactions on Graphics (TOG)*, vol. 29, ACM, 102.