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Unsupervised 3D shape segmentation and co-segmentation via deep learning

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ABSTRACT

In this paper, we propose a novel unsupervised algorithm for automatically segmenting a single 3D shape or co-segmenting a family of 3D shapes using deep learning. The algorithm consists of three stages. In the first stage, we pre-decompose each 3D shape of interest into primitive patches to generate over-segmentation and compute various signatures as low-level shape features. In the second stage, high-level features are learned, in an unsupervised style, from the low-level ones based on deep learning. Finally, either segmentation or co-segmentation results can be quickly reported by patch clustering in the high-level feature space. The experimental results on the Princeton Segmentation Benchmark and the Shape COSEG Dataset exhibit superior segmentation performance of the proposed method over the previous state-of-the-art approaches.

1. Introduction

Automatic segmentation of 3D shapes is a fundamental operation in geometric modeling and shape processing (Wu et al., 2013). It helps shape understanding and is also central to many computer graphics problems, including mesh parameterization, skeleton extraction, resolution modeling, shape retrieval and so on. Most of existing segmentation algorithms partition a single 3D shape depending on a specific kind of signature that is often invariant to a certain transformation group (Veltkamp and Hagedoorn, 2001; Hong and Soatto, 2015).

Known signatures include scale-invariant heat kernel signatures (SIHKS) (Bronstein and Kokkinos, 2010), shape diameter function (SDF) (Shapira et al., 2008), Gaussian curvature (GC) (Gal and Cohen-Or, 2006) and so on. To our knowledge, they can be used for shape segmentation purpose. However, shape understanding is a complicated task and thus we can't rely on a single signature to settle the segmentation problem once and for all. This is due to the fact that a signature, represented as a statistics or deterministic function, can only characterize the geometric shapes from a special perspective.

Recently, researchers find that simultaneously segmenting a set of 3D shapes within the same class into consistent decompositions, i.e., *co-segmentation*, is possible to achieve a better segmentation result than the traditional segmentation that is targeted at a single object. Some of these algorithms (Kalogerakis et al., 2010; van Kaick et al., 2011) require labeled train-

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0167-8396/

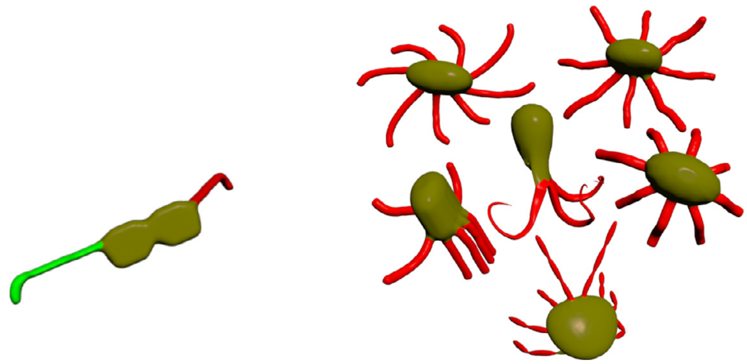
(a) (b)

Fig. 1. The experimental results of our approach. (a) Segmentation of a single shape. (b) Co-segmentation of a family of similar shapes.

ing data to learn common segmentation rules. Generally speaking, the supervised algorithms are able to produce a desirable segmentation result if the labeled data set is sufficiently large. However, labeling 3D shapes is pretty time-consuming and tedious. By contrast, the unsupervised methods (Sidi et al., 2011; Huang et al., 2011; Hu et al., 2012; Meng et al., 2013; Wu et al., 2013) can segment 3D shapes automatically, without extra labeling. Generally, it has to be at the cost of segmentation performance.

In this paper, we propose an effective unsupervised method for shape segmentation/co-segmentation based on deep learning. In the very beginning, we decompose each 3D shape into primitive patches to generate over-segmentation and compute various shape signatures for the input models. The signatures used in this paper include SIHKS (Bronstein and Kokkinos, 2010), SDF (Shapira et al., 2008) and GC (Gal and Cohen-Or, 2006). However, each separate signature can only characterize part of geometric features. Therefore, in the next stage, we build a deep neural network for unsupervised learning such that high-level features can be extracted from the geometric signatures computed in the first stage. It's noted that this stage doesn't need a labeling operation. With the support of unsupervised deep learning, we can finally segment models guided by the high-level features. Fig. 1 shows an example of segmentation and co-segmentation computed by our approach.

We evaluate our approach on two open datasets, including the Princeton Segmentation Benchmark (Chen et al., 2009) and the Shape COSEG Dataset (Wang et al., 2012). Extensive experimental results exhibit the superior segmentation/co-segmentation performance of the proposed method over the previous state-of-the-art approaches.

Contributions. Our contributions are twofold.

- We introduce deep learning into the problem of shape segmentation and co-segmentation such that various shape signatures can be integrated into a high-level feature space. This algorithmic framework is extensible – it supports a variety of shape signatures and hopefully achieves better segmentation results if some new signatures are considered in this framework.
- Our method is data-driven but does not need a tedious labeling process. The new approach, in its nature, is also adaptive to different databases.

The remaining of the paper is organized as follows. Section 2 reviews the related work on model segmentation and shape descriptors. Section 3 presents the overall segmentation framework followed by detailed construction process of high-level features. The unsupervised deep learning technique is detailed in Section 4. After that, we give the segmentation and co-segmentation algorithm in Section 5. In Section 6, we show extensive experimental results, as well as comparisons with the state of the art. Finally, we give limitations and future work in Section 7 and conclude this paper in Section 8.

2. Related work

2.1. 3D shapes segmentation and co-segmentation

Shape segmentation (Attene et al., 2006; Shamir, 2008) aims at segmenting a 3D shape into meaningful parts and plays an important role in shape analysis and shape understanding. So far, a lot of methods have been proposed for solving this problem. A common practice is to build a shape signature by extracting a kind of geometric properties and then apply it in shape segmentation using some decomposition techniques, such as approximate convexity analysis (Kaick et al., 2014), concavity-aware fields (Au et al., 2012), extreme learning machine (Xie et al., 2014), spectral clustering (Rong and Hao, 2004), K-Means (Shlafman et al., 2002), core extraction (Katz et al., 2005), graph cuts (Golovinskiy and Funkhouser, 2008; Katz and Tal, 2003), random walks (Lai et al., 2008), randomized cuts (Golovinskiy and Funkhouser, 2008), normalized cuts