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Unsupervised co-segmentation of 3D shapes via affinity aggregation spectral clustering

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ABSTRACT

Many shape co-segmentation methods employ multiple descriptors to measure the similarities between parts of a set of shapes in a descriptor space. Different shape descriptors characterize a shape in different aspects. Simply concatenating them into a single vector might greatly degrade the performance of the co-analysis in the presence of irrelevant and redundant information. In this paper, we propose an approach to fuse multiple descriptors for unsupervised co-segmentation of a set of shapes from the same family. Starting from the over-segmentations of shapes, our approach generates the consistent segmentation by performing the spectral clustering in a fused space of shape descriptors. The core of our approach is to seek for an optimal combination of affinity matrices of different descriptors so as to alleviate the impact of unreliable and irrelevant features. More specially, we introduce a local similarity based affinity aggregation spectral clustering algorithm, which assumes the local similarities are more reliable than far-away ones. Experimental results show the efficiency of our approach and improvements over the state-of-the-art algorithms on the benchmark datasets.

1. Introduction

Recently, there has been an increasing interest in shape co-analysis. The premise is that we can extract more knowledge by simultaneously analyzing a set of shapes, rather than an individual shape. The main task of co-analysis is *co-segmentation*, which simultaneously segments all the shapes in the input set in a consistent manner. The consistent segmentation has demonstrated great utility in modeling [1,2], shape retrieval [3,4], texturing [5], etc.

Many methods have been designed for shape co-segmentation [5–11]. In this paper, we focus on unsupervised co-segmentation, where no prior information is given and the entire knowledge must be extracted from the input set. Previous attempts in unsupervised co-segmentation can be classified into alignment-based and descriptor-based. In the alignment-based setting [6,7], the correspondences among different parts are constructed by a global alignment. Since parts with similar semantics can be rather dissimilar geometrically as well as topologically, these methods cannot handle shape sets with large variations. The descriptor-based methods [8,9,11] employ multiple feature descriptors to measure the similarity of parts, and obtain consistent segmentations by clustering the descriptor space. Since the descriptors are independent of the pose and location of shapes, they can handle shapes with rich variations in part composition and geometry.

Different shape descriptors describe different aspects of the geometric characteristics, and often provide complementary information. Fig. 1 shows an example, where the geodesic distance to the base of the shape (GB) is more reliable than the shape diameter function (SDF) for discriminating semantic parts in Fig. 1(a,b), while SDF is more reliable than GB in Fig. 1(c,d). Thus, simply concatenating them into a single vector might contain high degree of unreliable, and redundant information. The consistent segmentation obtained by clustering this kind of vectors may be not-optimal. However, with the exception of [9], co-segmentation methods do not address the feature selection or feature weighting in an unsupervised setting.

In this paper, we propose an approach to fuse multiple descriptors for descriptor-based unsupervised co-segmentation of a set of shapes from the same class. The proposed approach is based on the affinity aggregation spectral clustering (AASC) [12], which extends the spectral clustering to the setting where multiple affinities matrices are available. This algorithm can automatically weight each descriptor properly and aggregate multiple affinity matrices to construct a better one.

By assuming that the local similarities (high values) are more reliable than the far-away ones [13], we construct a sparse affinity matrix based on *k*-nearest neighbor graph. The resulting affinity matrix not only captures the core structure of the feature but also partially removes the unreliability, in comparison to the original one. With that, our local similarity based AASC can effectively combines the strengths of different descriptors, see Fig. 2.

Compared with the subspace clustering approach [9], our approach has two differences. First, our approach explicitly

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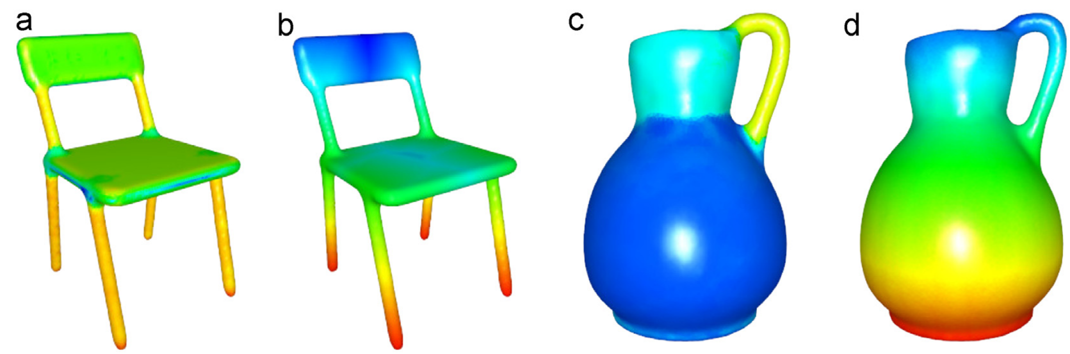

Fig. 1. SDF and GB defined on a chair and vase, respectively. The back and the seat of the chair are quite similar in SDF (a), while they differ a lot in GB (b); the handle is similar with neck in GB (d), but quite different in SDF (c). Hence, different descriptors for different shape categories should be assigned with different weights.

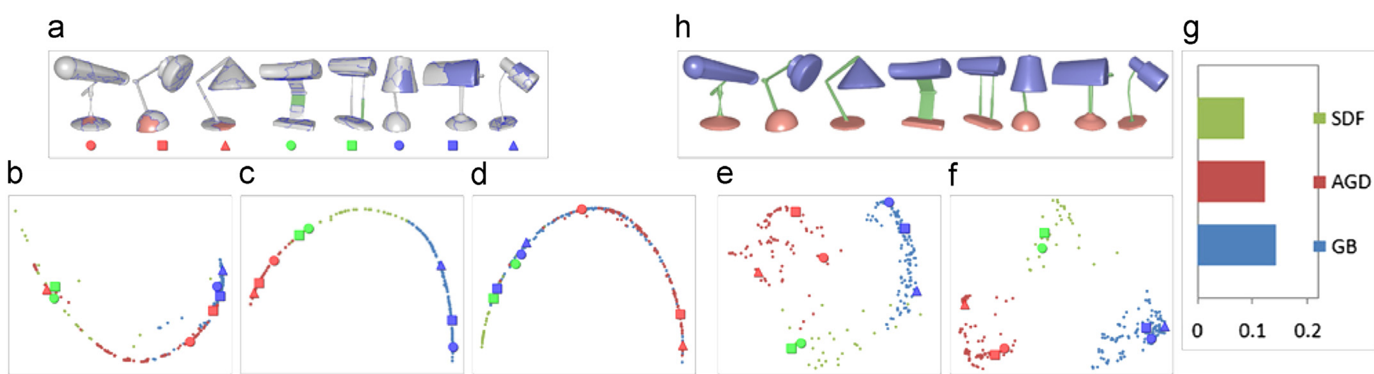

Fig. 2. Overview of the steps in our co-segmentation: (a) an over-segmentation is computed for each shape. (b,c,d) The 2D spectral spaces of affinity matrices based on the three computed descriptors, where each patch is corresponding to a point in such spaces. Three parts are mixed together in SDF and AGD spaces (b,d), while they fall in different ranges but not clearly separated in GB space. (f–h) Our fused space (f) with different weights for each descriptor (g), where the parts are clearly separated, resulting in the segmentation in (h). (e) In comparison, the 2D spectral space of the affinity matrix of the descriptor generated by concatenating three descriptors together, where the bottom and body of the lamp are mixed.

weights each feature and provides an explicit form of the learned affinity, while [9] finds a low dimensional representation of each feature for concentrating all affinity matrices together. Second, our approach integrates the feature selection and spectral clustering into an unified procedure, while [9] works in a two-step procedure. To some extent, our approach is similar with the learning based approach [5], where JointBoost classifier automatically computes the weight of each feature in the classification.

We evaluate our approach on various shape categories and make comparisons with state-of-the-art approaches. The results show that our approach performs better. Since our approach unifies the feature selection and spectral clustering together, it is more efficient than the previous methods. In summary, our contributions are twofold.

- We propose an unsupervised metric weighting method for shape co-segmentation, which simultaneously clusters the descriptor space to generate the consistent segmentation and weights each descriptor.
- We improve the affinity aggregation spectral clustering algorithm with the local similarities, which guarantees the consistency of the co-segmentation results.

2. Related work

Shape segmentation is a fundamental problem in shape analysis, which refers to decomposing a 3D shape into meaningful parts. Classical shape segmentation approaches focus on finding simple geometric criteria for segmentation of a single input mesh [14]. Although a variety of approaches have been proposed, no segmentation algorithm is known to produce high quality results for all classes of shapes [15]. One reason is that the individual shape may not provide enough geometric cues to distinguish its meaningful parts.

Recently, researchers have proposed to rather analyze sets of shapes and compute their consistent segmentation. Compared to traditional segmentation approaches, consistent segmentation not only partitions the shapes into segments, but also consistently labels the segments across the set.

Early work by Golovinskiy and Funkhouser [6] builds reliable correspondences across shapes using shape alignment and then clusters the shape faces according to an underlying graph. The graph links faces that are adjacent in the models and faces that establish a correspondence among different meshes after alignment. To deal with non-homogeneous part scales, Xu et al. [7] factor out the scale variation in the shape parts by clustering the shapes into different styles, which is defined as the scales of the shape parts. However, these approaches are limited to the shapes that can be properly aligned.

Kalogerakis et al. [5] present a supervised method to simultaneously segment and label shapes. Given a training set with enough pre-analyzed shapes, a model is learned with hundreds of geometric descriptors and then assigns labels to the new shape based on its descriptors. To enhance the correspondence among parts, van Kaick et al. [16] augment the supervised segmentation with content-driven analysis via a joint labeling approach. However, these methods require a substantial number of manually labeled training shapes. This poses a challenge since users are required to manually create training sets.