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Progressive 3D shape segmentation using online learning☆

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HIGHLIGHTS

- A progressive interactive 3D shape segmentation method is proposed.
- Online learning is adopted to train the segmentation model accumulatively.
- The segmentation model can be updated incrementally when new shapes are added.
- Segmentation can be more accurate with the increasing of the segmented shapes.

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ABSTRACT

In this article, we propose a progressive 3D shape segmentation method, which allows users to guide the segmentation with their interactions, and does segmentation gradually driven by their intents. More precisely, we establish an online framework for interactive 3D shape segmentation, without any boring collection preparation or training stages. That is, users can collect the 3D shapes while segment them, and the segmentation will become more and more precise as the accumulation of the shapes.

Our framework uses Online Multi-Class LPBoost (OMCLP) to train/update a segmentation model progressively, which includes several Online Random forests (ORFs) as the weak learners. Then, it performs graph cuts optimization to segment the 3D shape by using the trained/updated segmentation model as the optimal data term. There exist three features of our framework. Firstly, the segmentation model can be trained gradually during the collection of the shapes. Secondly, the segmentation results can be refined progressively until users' requirements are met. Thirdly, the segmentation model can be updated incrementally without retraining all shapes when users add new shapes. Experimental results demonstrate the effectiveness of our approach.

1. Introduction

Segmentation of 3D shapes into meaningful parts is a fundamental problem in shape analysis and processing. Numerous tasks in shape processing, 3D modeling, animation and texturing of 3D shapes benefit from consistent segmentation of shapes into parts [1,2]. A large number of segmentation methods have been proposed, and most of them pay attention to segmenting an individual shape based on geometric features such as convexity and curvature [1,3,4]. Although a variety of geometric features have been investigated, no single feature or collection of features is known to produce high-quality results for all classes of shapes [1], and consistently segmenting a set of shapes remains challenging [5].

Accordingly, more and more researchers have been focusing on segmentation methods based on shape set to partition the 3D shapes consistently [6–8]. The shapes in this shape set belong to the common family, and they share the same functionality and general form [7]. By utilizing this characteristic, the segmentation methods based on shape set can generate segmentation carrying consistent semantics across shapes.

They can be classified into three categories: supervised, unsupervised and semi-supervised. The supervised methods can employ the information learned from the labeled training set to segment a given shape [6,9], and obtain significant improvement over single-shape segmentation methods. However, they require a large number of manually segmented and labeled training shapes to learn from, and they have to retrain on the whole training set, when there are only a small amount of new shapes submitted to the training set. Moreover, the segmentation mode, such as the specific scope, number and categories of consistent parts to be segmented, is utterly determined by the training set and can hardly be changed by users.

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The unsupervised ones process the shapes from an input set in a batch, and simultaneously segment these shapes into consistent parts [5,7,10–15]. They do not require any labeling process for the shape set, but they still have to collect a number of shapes to perform the algorithm. And they also need performing the algorithm over the whole pipeline for the updating of the shape set. In addition, although the number of consistent parts can be specified by users, the scope and categories are still determined by the algorithm.

The semi-supervised ones use information from both labeled shapes and unlabeled ones, which improve the results of unsupervised methods with the assistance of external input and overcome the difficulties of requiring a large amount of labeled shapes in the supervised methods [8,16,17]. Users' intention on the segmentation mode can be reflected in the results. However, the same as the supervised and unsupervised methods, they require preparing a number of shapes at the very beginning. Although some semi-supervised methods have considered about the segmentation of the new shape [16,17], the segmentation or labeling of the new shape cannot be helpful for other shapes. They still need to perform the algorithm on all the shapes including the new shape to achieve the set updating.

So overall, there are three challenges in the existing methods: firstly, they have to collect a number of shapes before performing the segmentation algorithm to achieve satisfactory results; secondly, they are shortage of some efficient updating strategy that they must perform the algorithms on all the shapes when there are only a small amount of new shapes added to the shape set; thirdly, the segmentation does not necessarily convey the users' intention.

In this paper, we propose a novel method, which can progressively segment a 3D shape using online learning. A segmentation model is trained/updated progressively by Online Multi-Class LPBoost (OMCLP) [18], where several Online Random forests (ORFs) [19] are trained as the weak learners. Then, graph cuts optimization [20] is performed to segment the 3D shape, the trained/updated segmentation model is used as its data term.

The features of this method lie in three aspects. The first one is that the segmentation model can be learned online. In the initial stage, users can submit a 3D shape and label on this shape according to their intention. The segmentation model can be learned initially based on these labels, and used to segment this submitted shape. Users then correct the initial segmentation results. And the segmentation model can be further learned iteratively based on the correction. As the new shapes are submitted occasionally, the segmentation model can be formed gradually during the online learning process. The second one is that users can refine the segmentation results in an online way. During the whole pipeline, users can correct the false-labeled regions in the segmentation. And the refined segmentation can be obtained according to these regions. Users can continue correct this refined segmentation result until it meets their requirements. The third one is that the segmentation model can be updated online. When the new shapes are submitted, the segmentation model can be updated efficiently without retraining on all the shapes.

Our approach has four advantages.

1. The segmentation model can be learned gradually as the shapes are segmented. So, it does not need any explicit shape collecting or training stages in our method.
2. It provides users an easy and intuitive way to interact through the segmentation process. They can correct the segmentation by simply click at the false-labeled parts of the shape. And with the increasing of the user interactions and accumulation of the shapes, the segmentation of the submitted shapes will become more and more precise.
3. The segmentation model can be updated easily when new shapes are added into the shape set. Updating is an important task in learning based methods, no matter supervised or unsupervised ones. The existing methods are lack of some updating scheme, so they usually have to perform their algorithms on the whole shape set repeatedly.
4. Users can segment the 3D shapes according to their intention. They can direct the segmentation mode including the scope, number and categories of consistent parts during the segmentation.

We evaluate the presented approach on several 3D shapes, and the experimental results demonstrate the above advantages of our method.

2. Related work

We review the previous work in several related categories: segmentation of individual shapes, segmentation based on shape set, interactive segmentation, and online learning.

2.1. Segmentation

Shape segmentation is a fundamental problem in shape analysis, which refers to decomposing an individual 3D shape into meaningful parts. Recent surveys can be found in [3,4], and comparisons of several methods appear in [1]. These methods use techniques such as K-means [21], graph cuts [22], hierarchical clustering [23], primitive fitting [24], random walks [25], and spectral clustering [26]. And they aim to partition the individual shape into segments based on some simple geometric criteria: convexity [27], curvature [28] and so on. Although a variety of geometric features have been investigated, no single feature or collection of features is known to produce high-quality results for all classes of shapes [1], and consistently segmenting a set of shapes remains challenging [5]. Therefore, more and more researchers have been focusing on segmentation methods based on shape set to partition the 3D shapes consistently.

2.2. Segmentation based on shape set

These works can be classified into three categories: supervised, unsupervised and semi-supervised. In the supervised case, they employ the information learned from the labeled training set to segment a given shape. Kalogerakis et al. [6] use the Conditional Random Field (CRF) model trained by a collection of labeled shapes to segment and label a given 3D shape. van Kaick et al. [9] further use this knowledge to establish a part correspondence between a pair of shapes. Benhabiles et al. [29] learn a boundary edge function from a large database of manually segmented 3D shapes, to segment any input 3D shape. A significant improvement in correctness over single-shape segmentation methods is demonstrated in these supervised methods. However, they require a large number of manually segmented and labeled training shapes to learn from, and they have to retrain on the whole training set, when there are only a small amount of new shapes submitted to the training set. Moreover, the segmentation mode, such as the specific scope, number and categories of consistent parts to be segmented, is utterly determined by the training set and can hardly be changed by users.

The unsupervised methods process the shapes from an input set in a batch, and simultaneously segment these shapes into consistent parts. Kreavoy et al. [30] first segment each shape in the set individually into parts with similar segmentations, and then create a consistent segmentation by matching the parts and finding their correspondences. Huang et al. [11] present a novel linear programming approach to jointly segment the