Computer-Aided Design 55 (2014) 13–25

Contents lists available at ScienceDirect

Computer-Aided Design

journal homepage: www.elsevier.com/locate/cad

Shape recognition of CAD models via iterative slippage analysis[☆]

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HIGHLIGHTS

- We present a new shape recognition method by iterative slippage analysis.
- The exact normal is found to be one of the key points for slippage analysis.
- The appropriate region is found to be the other key points for slippage analysis.
- A knowledge guided region growing method is used to get the appropriate region.
- An iterative normal modification method is used to obtain the exact normal.

ARTICLE INFO

Article history:
Received 31 July 2012
Accepted 28 April 2014

Keywords:
Shape recognition
Slippage analysis
Basic primitives

ABSTRACT

A new slippage analysis method for recognizing basic primitive surfaces of CAD models is presented in this paper. Obtaining the exact normal and searching the appropriate local region of each point are found to be the key steps for determining the local slippage motion type. First, the tensor voting-based boundary point recognition method is integrated to preprocess the original points. Then, the local slippage analysis method is used to initialize the point type. Furthermore, the appropriate region of each point is acquired by the region growing method. Meanwhile, the middle level information (the basic primitive surface types and the representative parameters) is found, guiding the modification of the normal of each point and the iterative detection of the surface types. Finally, the middle level information-based smooth method is introduced to refine the boundary of each basic primitive surface. The empirical results show that the proposed algorithm is efficient and robust for recognizing primitive shapes from CAD models of mechanical parts.

1. Introduction

With the rapid development of 3D digital data acquisition devices, we can obtain all the point cloud of 3D models easily and rebuild the triangular meshes with high accuracy. This is recently called reverse engineering, which provides a new way to create massive complex 3D models. However, due to the loss of middle level and high level model information (symmetry, parallelism, perpendicularity, etc.), such meshes are too raw to be directly used in the subsequent processes, such as CAD model reconstruction, and convergent-type CAE. With the virtual explosion in the amount of raw data available for designer, the critical problem shifts to obtain the middle level and high level information through this data and adopt it to improve the efficiency for redesigning a new product [1]. The key processes to detect the middle level and high level model information from existing 3D point clouds are mesh segmentation and shape recognition [2–6].

Recently, a lot of researches have been done on shape segmentation and recognition. Most previous approaches are based on the local model information like curvature or boundary detection. However, even with the segmented surface patches, it is also difficult to get the middle level model information, let alone the high level model information. Realizing that a lot of mechanical parts consist of basic primitives, such as plane, sphere, cylinder, cone, extrusion, revolution, helix, nowadays, many researchers have attempted to segment the CAD models into basic primitives [7–13]. The existing primitive shape fitting approaches likely confront the following problems: (1) hardly can recognize all the basic primitives, such as plane, sphere, cylinder, cone, extrusion, revolution, and helix; (2) hardly can obtain the middle level information of the basic primitives, such as the center and radius of a sphere, the normal and position of a plane, etc; (3) sensitivity to numerical

☆ This paper has been recommended for acceptance by Karthik Ramani, PhD.

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http://dx.doi.org/10.1016/j.cad.2014.04.008

noise inherently embedded within the obtained 3D point clouds. Therefore, we propose a new slippage analysis method to robust recognize shape primitives of mechanical parts. We discover that the key processes for slippage shape segmentation are the exact normal and the appropriate region selection of each point. The existences of noise in point cloud obtained by 3D digital data acquisition devices and sharp edges in mechanical objects make it difficult to find the exact normal of each point. Thus, we introduce the tensor voting method to classify the point type into a plane, a sharp edge and a corner. Meanwhile, the detected point type improves the efficiency of the surface type segmenting and recognizing. Furthermore, we use the knowledge-based region growing method to get the exact region for each primitive patch, and then adopt the extended RANSAC method to obtain the middle level information, which iteratively guides the normal modification and the shape recognition.

2. Related work

Mesh segmentation has been extensively studied in the past years. The goal of segmentation is to cluster the mesh model into meaningful parts. However, it is hard to propose a segmentation approach that can segment all kinds of models into appropriate parts, due to the application field difference [14,15]. In computer graphics, the region growing method, the watershed method, the K-means method, the mesh shift method, the shape diameter function method, and the rand walk method have been well studied [16–21]. But these approaches cannot be directly applied to segment mechanical parts. Várady et al. [2] provide a detailed survey in the reconstruction of mechanical parts and underline that the surface type recognition and surface fitting are the specific issues for reconstructing a B-rep model. Agathos et al. [22] present an exhaustive overview of 3D mesh segmentation both on surface-based methods, which segment the part into basic primitives, and on volume-based methods, which segment the part into different volumes or features. We roughly group the related works into three categories: low level information-based surface segmentation, middle level and high level information-based shape classification, and robust shape recognition.

Low level information-based surface segmentation. Many traditional segmentation methods use the local level information such as the Gaussian curvature or the mean curvature to segment the model. One of the most popular segmentation methods is region growing. This method selects a set of seed points and merges the neighbor points to a patch which has the same local properties, such as principle curvatures. However, it is difficult to find the exact seeds and there will be over segmentation in the transition of two patches [23,24]. Lavoué et al. [25,26] extend this algorithm by using a robust curvature tensor to guide the region growing and introduce a boundary score to rectify the patch boundaries. Kim et al. [27] introduce the tensor voting-based mesh segmentation method. The point type is recognized first by the robust tensor voting theory. Then, the mesh data with additional attribute such as color information is clustered into several patches by the k-means algorithm. However, the local information-based region growing method cannot segment all the basic primitives, and it is much difficult to obtain the middle level and high level information of mechanical parts.

Middle level and high level information-based shape classification. Recently, many researches have realized that shape features play important roles in the segmentation of man-made objects. Cohen-Steiner et al. [28] propose a segmentation algorithm, called variation shape approximation. This algorithm iteratively fit planes and partition triangles to the regions until the convergence. Wu et al. [29] extend this algorithm by using not only planes, but also cylinders, spheres, and rolling ball surfaces for the fittings. Yan et al. [11,12] propose an iterative method for mesh segmentation by fitting quadric surfaces. However, these methods partition the entire surface into parts approximated by shape proxies; thus the complex surface will also be assigned primitives. Attene et al. [8,9] introduce a hierarchical mesh segmentation method to detect primitive geometries. The algorithm generates a binary tree of clustering and iteratively merges the local neighbor points into one single primitive cluster based on the approximation method. These fitting approaches require users to input the number of regions first, but it is difficult to find the appropriate number of regions before mesh segmentation. Protopsaltis et al. [30] introduce the planar cross section to reconstructing CAD models from the point clouds. However, the cross section should be along a principal axis, and the feature intersections and cross section along a sweep trajectory are ignored. Sellamani et al. [31] propose a robust method to approximate sweep shape by using prominent cross section. Goyal et al. [32] adopt the prominent cross section to extract high level, volumetric information from mesh models. However, it is difficult to reconstruct a mechanical part with multiple sweep components and intersections between them. Furthermore, the manufacture and function features of mechanical parts are composed of basic geometry primitives; thus, the classified sweep components need further process to be converted to semantic manufacture features.

Robust primitive shape recognition. Most of traditional mesh segmentation methods aim to segment the surface into different parts, and some try to classify the mesh by the surface type. However, how to robust recognize the primitive shape from point clouds is challenging. Benjamin et al. [33] propose a heat walk algorithm to segment triangle meshes, which is robust to a variety of noise factors. Fang et al. [34] adopt the heat mean signature to robust segment the surface which satisfies the perceptually consistent mesh segmentation conditions. However, the heat kernel-based method cannot be used to segment the mechanical parts into basic primitives. Golovinskiy et al. [35] propose a system for recognizing objects in 3D point clouds of urban environments. The graph-cut algorithm is adopt to segment the point clouds into different patches, and then a trained classifier model is used to recognize the segmented patches. However, it is difficult to propose an appropriate shape features that can recognize all the objects from the point clouds. Lafarge et al. [36] proposed a multi-label Markov Random Field formulation, which is based on the principle curvature, to segment the surface into patches, and then use a primitive-fitting method to classify the basic primitives. However, this method is less competitive for recognizing shape from models, which are strongly corrupted by noise. Décoret et al. [37] extend the standard Hough transform and employ it to identify planes for billboard clouds of triangle meshes. However, this method exhibits poor run-time performance on recognizing basic primitive from large or complex mechanical part because of the high computational demand of the Hough transform. Schnabel et al. [10] present a shape detection method in point cloud based on the RANSAC method. They demonstrate a robust algorithm that used random samples and the middle level information to cluster basic primitive shapes. However, the basic primitives adopted in this method are not suitable for building all the mechanical models. Gelfand et al. [13] propose a slippable motion-based hierarchical clustering method. They introduce a rigid motion to segment mechanical objects into planes, spheres, cylinders, linear extrusion surfaces, surfaces of revolution and helical surfaces. We certify that the exact normal estimation and the choice of neighborhood point set of each point are the key tips for the slippage-based segmentation method theoretically and practically, and employ the RANSAC method to obtain the middle level parameters of each basic primitive, guiding the modification of the normal of each point and the iterative shape recognition of mechanical parts.