Applied Mechanics and Materials *Online: 2012-11-12*
ISSN: 1662-7482, Vols. 215-216, pp 660-663
doi:10.4028/www.scientific.net/AMM.215-216.660

A Novel Mesh Segmentation Method for Conventional Engineering Parts in Reverse Engineering

Peng-xin Liu[1, a], Xuan Liu[2,b] and, Ping Liu[1,c]

[1] Tianjin Key Laboratory of High Speed Cutting and Precision Machining, Tianjin University of Technology and Education, Tianjin, China, 300222
[2] Shanghai Ocean University, Shanghai, China, 200030

[a]lau.panthea@gmail.com, [b]xliu@sohu.edu.cn, [c]ping_liu@eyou.com

Keywords: Reverse engineering, Mesh segmentation, Conventional engineering parts, Mean shift

Abstract. In this paper a step segmentation method for conventional engineering parts which usually comprise by simple analytic surfaces and are important investigation objects of reverse engineering is proposed. In the first segmentation fourteen directions are chosen initially, and a k-mean algorithm according to the normal vectors is used, then the surface is divided to form patches by a region-growing scheme. In order to identify simple analytic surface, curvedness of a patch is set as the criterion by which the surface merged into near constant curvedness region. Especially a novel mean shift algorithm is adopted in this method, that a powerful technique for clustering in image process, and is extended to normal filtering while preserving the features to increase robustness of the method. Experimental evaluations using scan data or noise data demonstrate the efficiency of the proposed method.

Introduction

Reverse engineering is a design process going from a physical or clay model to a digital model, when some existing object has not been originally described using a CAGD system. First a triangular mesh is created which reflects the basic topology of the final model and remains a preferred representation for surface data because of its ability to approximated complex shapes and visualization efficiency. After that is the segmentation to partition the mesh into smaller meaning parts depending on applications.

Mesh segmentation, that is, the grouping of the original triangular mesh into submeshes usually based on certain metric properties of vertices that comprise the mesh. Past approaches fall into two main categories: edge-based approach [1] and region-based approach [2]. Both classes of approaches have their strengths and weakness and usually need post-processing phases. Edge-based methods tend to produce gaps in the boundaries of regions. On the other hand, region-based methods can be easily perturbed in the presence of noise and generate boundaries which are connect but generally distorted .In addition, finding suitable initial seed may be nontrivial. The success of mesh segmentation algorithms judged based their ability to provide meaningful partitions which user need.

Analytic surfaces occur more frequently in mechanical engineering. In fact, 85 percent of all mechanical pieces are well described by patches of planes, cones, spheres and cylinders [3]. The simpler surface can be detected in a more reliable and efficient manner. However, in practice situation, to implement it is a real challenge because of the noise contaminated in the mesh. Therefore, this paper proposes an effective and robust segmentation technique for conventional engineering parts.

Mesh Segmentation based Mean Shift

Mean shift algorithm has a wide variety of application in the field of computer vision and pattern recognition [4]. In the following we describe how to apply it to normal filtering.

Given n data points x_i, $i = 1,\ldots,n$ on a d-dimensional space R^d, the multivariate kernel density estimate obtained with kernel function $K(x)$ and bandwidth h is

$$f(x)=\frac{1}{nh^d}K(\frac{x-x_i}{h}) \quad (1)$$

For radially symmetric kernels, it suffices to define the profile of kernel $k(x)$ satisfying

$$K(x)=c_{k,d}k(\|x\|^2) \quad (2)$$

Where $c_{k,d}$ is a normalization constant which assures $K(x)$ integrates to1.The modes of the density function are located at the zeros of the gradient function $\nabla f(x)$ .Then the so-called mean-shift vector Eq. 3 is deduced by the gradient of the density estimator Eq. 1,

$$m_h(x)=\frac{\sum_{i=1}^{n}x_i g(\left\|\frac{x-x_i}{h}\right\|^2)}{\sum_{i=1}^{n}g(\left\|\frac{x-x_i}{h}\right\|^2)}-x. \quad (3)$$

Where $g(x)=-k^{'}(s)$. The mean shift vector always points toward the direction of the maximum increase in the density. For clustering $S=\{x_1,x_2,...,x_n\}$ with mean shift, the following two steps are performed for each $x_i\in S$: (1) Computation of the mean shift vector $m_h(x^t)$ according to Eq. 3; (2) Translation of the window $x^{t+1}=x^t+m_h(x^t)$ until convergence. The points which are in the same mode are associated with the same cluster.

In this research, one simple extension of the above procedure consists of dealing with a triangle set { t_i }.We consider triangle normals { n_i } as scattered data $\chi=\{x_i=ni\,|\,ni\in \mathrm{N}\}$ in $\mathbb{R}^3$ .It is convenient to use mean shift procedure and Gaussian kernel is chosen. To accelerate the mean shift computation, constructing a k-D tree is the most common method. This study used the topology information of the triangle mesh for the accelerating query process.

Once the mesh normals are prefiltered with mean shift, triangles of the mesh are classified according to their normal. The clustering is done via a K-Means algorithm, namely, a fast least-squares partitioning method which allowing to divide triangles into k-groups. The initial generators are chosen to be fourteen unit vectors including six directions of Cartesian Coordinates and eight diagonal directions of unit cubes. At the end of the algorithm each triangle is associated to a cluster C_i, $i=1,...,14$ .The label of each triangle is the index of the cluster to which it belongs.

In order to recovering the region consisted of triangles with same label, a region growing process is performed. First, a triangle T_i as seed is selected randomly, and is pushed into the queue Q. For its three adjacent triangles T_j, we check if their labels are the same as that of T_i respectively: if the label is different, T_j is chosen as the next growing seed; otherwise, we assign T_j to the region indicated by the label of T_i, and insert it in the queue Q.The region growing process is then performed by repeatedly popping triangles and checking their neighbors until the queue is empty. A region with the same label is obtained at the same time. Do this process until no new seed can be found.

Region Merging

After the initial segmentation, the region merging is a necessary step for reducing the over-segmentation resulting from the growing step and identify algebraic surface. Curvedness which is known as the bending energy is used as the shape descriptor. It measures the intensity of the surface curvature and describes how gently or strongly curved a surface is. Mathematically, it is defined as

$$C_V=\sqrt{(k_{\max}^2(v)+k_{\min}^2(v))/2} \quad (4)$$

Where $k_{\max}(v)$ and $k_{\min}(v)$ are the principal curvatures of the surface at vertex v and are estimated by the algorithm [5].

To merge adjacent similar regions, we construct a region adjacency graph (RAG) in which each node represents a connected subset of the mesh and each edge represents an adjacency between two regions. Edges are evaluated by a similarity distance DC_{ij}, computed as

$$DC_{ij} = \left\| c_i - c_{ij} \right\| + \left\| c_j - c_{ij} \right\| . \tag{5}$$

Where c_i and c_j are the average curvedness (not include boundary vertices of region) corresponding two adjacency region, and c_{ij} is the average curvedness of their boundary vertices. Fig.1 shows which is the available boundary vertices when computer c_{ij}. The merging of the graph is processed: the smallest edge of the graph is eliminated at each iteration, thus the corresponding regions are merged; then update the graph. When the weight of the smallest edge is larger than a given threshold, this graph reduction ends.

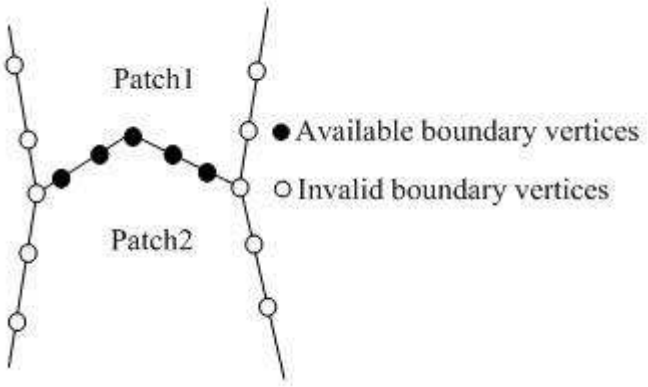
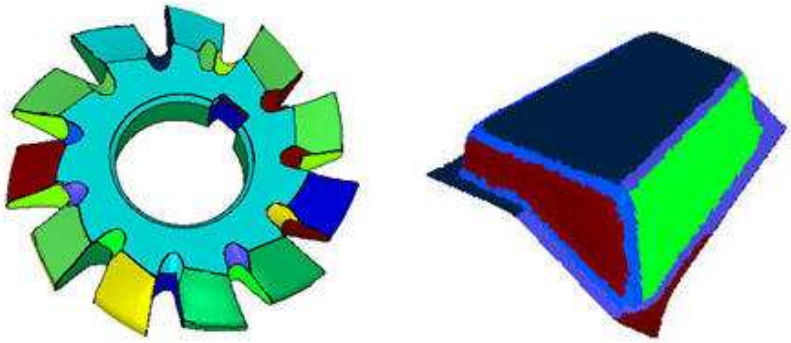


Fig.1 Representation of the available boundary vertices between Patch1 and Patch2

Result and Discussion

In this section, three models scanned in optical scanner were used to test the efficiency of the algorithm and the influence of noise. Different regions were depicted by randomly selected pseudo-color. First, example are given for two smooth mesh, gear cutter and pocket (see Fig.2). The decompositions are intuitively correct and adapted to the extraction of smooth regions and surface fitting objectives.

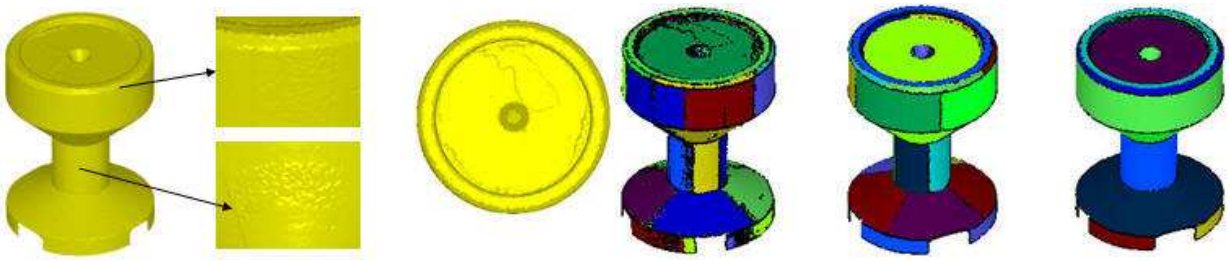


(a) (b)

Fig.2 The segmentation of smooth mesh.(a)Gear cutter.(b) Pocket

The noise contaminated in the data may come from measurement and form error. In this section, corrector models scanned in optical scanner was used to test the efficiency of the algorithm and the influence of noise. Fig.3(a) shows the segmentation result of our method applied to a noise corrector. Due to the characteristics of scanning devices employed, it is difficult to identify little sharp edges exactly, as shown in the top row of Fig.3 (b).The form errors which are introduced by post wear are shown in the bottom row of Fig.3 (b) and Fig.3 (c).From the comparison presented in Fig.3 (d) and Fig.3 (e), it is observed that our approach using mean shift exhibits strong advantage for a noise

model. The last segmentation result is shown in Fig3. (f). Finally, Table 1 presents the computational cost of the algorithm. All experiments were conducted on a PC, with an Inter(R) Pentium(R) 3.00GHz CPU.



(a) (b) (c) (d) (e) (f)

Fig.3 (a) The triangular mesh of a corrector. (b) Top: the measurement error of boundaries. Bottom: the form error. (c) The form error at top (d) Segmentation without mean shift (e) Segmentation with mean shift (f) Result after merging.

Table 1 Performance of the proposed algorithm

Model	Vertices	Mean shift [sec.]	Initial segmentation[sec.]	Region merging [sec.]	Patch No.
Pocket	5724	—	0.56	0.88	14
Gear cutter	27257	—	7.21	4.98	50
Corrector	35155	10.82	11.53	7.85	13

Conclusion

A step and robust segmentation method was provided using normal as a metric. The experiment results indicate that the normal filtering with mean shift can effectively deal with the noise, thereby show a robust segmentation result and the algorithm produces meaningful results for analytic surfaces .As part of future work, we plan to extend mean-shift to high order surface descriptors and split the region from the normal based segmentation to identify the borders where the tangent vector is continuous but the directional curvature is discontinuous.

Acknowledgements

This work was financially supported by Key Project of Chinese Ministry of Education (No.212056) and Tianjin University & Education Foundation (KYQD10015).

References

[1] J.Huang, C.H.Menq : IEEE Transactions on Robotics and Automation (2001) .

[2] A. P. Mangan : IEEE Transactions on Visualization and Computer Graphics (1999) .

[3] S. Petitjean: ACM Computing Survey (2002).

[4] K. Wua, M. Yang :Pattern Recognition(2007) .

[5] M. Meyer, M.Desbrun, P.Sechroder, et al : Visualization and Mathematics(2002) .