Chapter 11
Intelligent Systems for Volumetric Feature Recognition from CAD Mesh Models

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11.1 Introduction

Volumetric features are ubiquitous in mechanical engineering applications from design to manufacturing cycle. In many mechanical engineering parts, blends and holes constitute a significant percentage of features. Recognizing volumetric features in Computer Aided Design (CAD) mesh models are vital in applications such as mesh simplification, design, manufacturing, and finite element analysis.

Mesh models constructed from 3D scan data are called scan-derived mesh and those generated from B-rep models using CAD software are called CAD mesh models (CMM). The focus of this chapter is the CMM.

Segmentation aims to partition CMM into "meaningful" regions [1]. Each region can be fitted to a distinct, mathematically analyzable form [2]. Literature reveals the availability of many mesh segmentation algorithms. However, most of them are not suitable for CMM as scan-derived mesh is dense and streamlined whereas CAD mesh is sparse, non-uniform, and non-streamlined. Several mesh segmentation approaches in the literature have relied on information such as curvature or sharp edges. Huge time is needed for curvature computation. The curvature is sensitive to noise, variations in dimensions, and randomly disseminated triangulations [2]. It is

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difficult to establish one global threshold [3, 4] and so several mesh segmentation methods set local threshold while computing curvature.

The last three decades witnessed significant research work in extracting volumetric and free-form features. However, most feature recognition (FR) tools work on B-rep models while innovative design and manufacturing systems are mesh based [5, 6]. Therefore a need is exists to develop FR from the mesh model. STL (Standard triangulated language) is globally accepted by all CAD/CAM system which makes it platform-independent data exchange format [7]. If we recognize features from STL model, it will be a unique data translator service [8, 9].

Above observations have inspired the research work reported in this chapter. The hybrid mesh segmentation approach is used for detecting volumetric features. The propose algorithm segments the CMM into basic primitives like plane, cylinder, cone, sphere, or torus etc. After extraction of analytical surfaces, rule-based reasoning is used for FR. The innovation lies in the intersecting feature detection in which tedious curvature information and edge detection technique is not required. Further, the results are compared with existing and recent state-of-the-art approaches like Attene et al. [10], Schnabel et al. [11], Li et al. [12], Yan et al. [1], Adhikary and Gurumoorthy [13], and Le and Duan [14].

The main contributions of this research can be summarized as follows:

- Intelligent threshold prediction makes hybrid mesh segmentation automatic.
- Complex holes lying on multiple planer regions are detected and separated successfully.
- No curvature information is required for feature detection.
- Features are extracted without edge detection techniques.
- Partitioning criteria used for clustering triangles is "Facet Area."
- Intersecting features are extracted automatically, and their parameters are also estimated accurately.

The rest of the chapter is structured as follows: Sect. 11.2 provides a comprehensive review of relevant literature; Sect. 11.3 illustrates a proposed methodology for the volumetric feature recognition. Section 11.4 deals with volumetric feature recognition. Discussion based on results is provided in Sect. 11.5. Section 11.6 present conclusion and future scope.

11.2 Literature Review

A comprehensive review of various FR approach with their strengths and weaknesses are reviewed in the literature [6, 9, 15–19]. The focus of the current research work is to compare the robustness and consistency of hybrid mesh segmentation algorithm with existing and recent state-of-the-art approaches; the literature review is limited to those approaches only.

Attene et al. [10] designed a Hierarchical Fitting Primitives (HFP) technique of mesh segmentation which needs a number of clusters as an input criterion along with

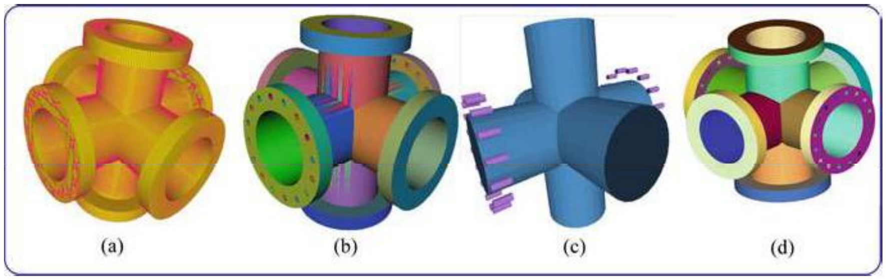

Fig. 11.1 Failure cases for intersecting volumetric feature, (**a**) Input CAD mesh model. (**b**) Attene et al. [10]. (**c**) Muraleedharan et al. [20]. (**d**) Output

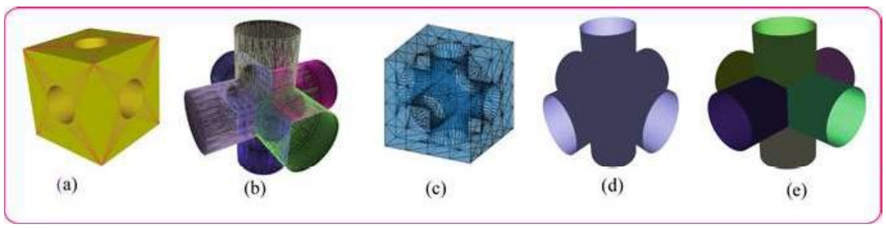

Fig. 11.2 Failure cases for interacting features, (**a**) input CAD mesh model. (**b**) Attene et al. [10]. (**c**) Adhikary et al. [13]. (**d**) Muraleedharan et al. [20]. (**e**) Output

visual inspection to carry out segmentation. However, knowing a number of clusters before feature extraction is difficult. Figures 11.1b and 11.2b show the failure case of Attene et al. [10].

Schnabel et al. [11] designed 'RANSAC' (RANdom Sample Consensus)-based framework for recognizing basic primitives. However, the approach either over-segments or under-segments the model. It results in inaccuracy of feature extraction. Li et al. [12] modified the approach of Schnabel et al. [11] and have developed the 'GlobFit' method. This approach is primitive fitting based rather than segmentation. They have used parallelism, orthogonality, and equal angle relations to extract primitives. This approach is computationally costlier and heavily depends on 'RANSAC' [11] output. Yan et al. [1] invented an algorithm for mesh segmentation of scanned or STL CAD model into non-overlapping patches by fitting quadric surfaces. Each patch was fitted to a general quadrics surface. Criteria used for segmentation was geometric distance based error function. However, the method is suitable for quadric surface only. It is not suitable to identify tori or blends.

Adhikary and Gurumoorthy [13] presented an algorithm to recognize free-form volumetric features without segmentation from CMM. They used 2D slicing to identify feature boundaries. Features are identified by extracting feature boundary edges using 3D seed information of those 2D features. Region growing technique is used to find features using 3D seed vertex and feature boundary edges. The algorithm does not depend on mesh geometrical properties and mesh triangle density. However, the algorithm is unable to detect and extract parameters of volumetric features for test case shown in Fig. 11.2a. Their algorithm depends on the choice of Minimum Feature Dimension (MFD) and must be known in advance before feature extraction. Figure 11.2c shows the failure case of Adhikary and Gurumoorthy [13].

Muraleedharan et al. [20] used a random cutting plane to extract the volumetric features. They blend graph traversal and Gauss map for FR. The algorithm is unable to separate the interacting features. Figure 11.1c shows the limitation of their approach. They used Gaussian curvature for boundary extraction and separating the interacting features. Their algorithm depends on a number of planes for features extraction which is assumed to be known. The feature must have the presence of inner rings which is the major limitation of the algorithm. If a feature does not have inner rings, it will not be detected. Figures 11.1c and 11.2d show examples of volumetric feature recognition but unable to separate into individual features. As feature joints have a complex boundary, segmentation is unable to separate them. However, the propose algorithm detects intersecting features along with geometric parameters.

Le and Duan [14] used uniform slicing along the major direction. They used a dimensional reduction technique which transforms 3D primitives to 2D in order to get a profile curve. The primitives are detected based on profile curve analysis. However, the algorithm is slice thickness dependent, and slicing techniques fail to detect or separate complex interacting features as noted by [13].

The proposed technique automatically extracts volumetric features like blends and holes along with their geometric parameters. With hybrid mesh segmentation, we can separate the interacting features as well. Figures 11.1d and 11.2e shows examples of volumetric feature recognition. Hybrid mesh segmentation recognized all the features whereas the closest one among others is the Le and Duan [14].

11.3 Methodology

The proposed algorithm involves three steps, viz. preprocessing, hybrid mesh segmentation, and volumetric feature recognition. Figure 11.3 illustrates the overall strategy to extract volumetric features from CMM which consists of the following steps:

11.3.1 Preprocessing

In preprocessing, topology is built in imported CAD mesh model, and automatic threshold prediction has been carried out.

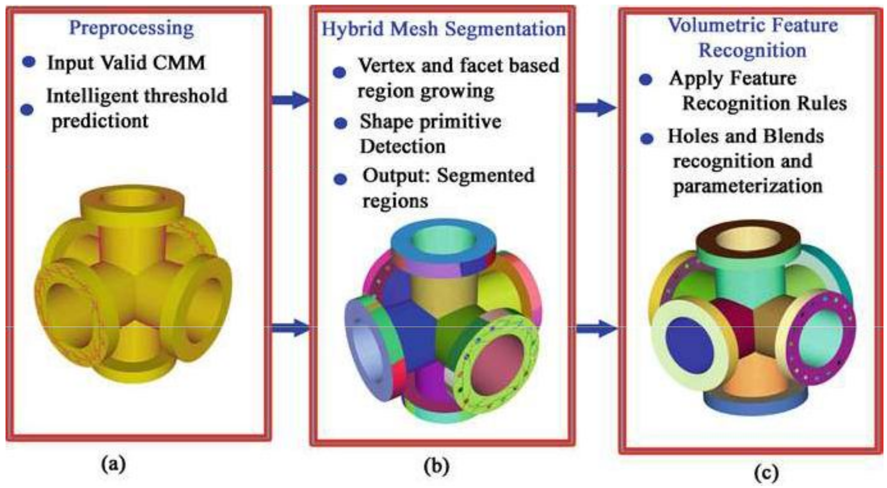

Fig. 11.3 The framework of the proposed methodology. (**a**) Preprocessing. (**b**) Hybrid mesh segmentation. (**c**) Volumetric feature recognition

11.3.1.1 Input CAD Mesh Model

In this research work, we assume a valid STL model as an input in ASCII (American Standard Code for Information Interchange) or Binary format which is free from errors, hence no need of model healing [9].

11.3.1.2 Automatic Threshold Prediction

The facets laying on the same surface have the same quality. We use the "Facet Area" property to segment the model. A significant step in segmentation is to set the appropriate Area Deviation Factor (threshold) at the beginning. It is a cumbersome task of identifying a threshold value for getting the expected results. Most of the time a trial-and-error approach is used to identify a correct threshold [20]. Inadequate threshold leads to over-segmentation (multiple small patches) or under-segmentation. Over-segmentation needs a post-processing merging step which increases processing time whereas under-segmentation leads to deficient results [21]. However, for a layman, setting the appropriate threshold is too complicated. Manual prediction is laborious and errors prone. Therefore, an automatic and intelligent prediction approach is of significance.

As stated above, Area Deviation Factor (ADF) is the decisive factor in segmentation quality. Intelligent prediction of threshold using the artificial neural network (ANN) and a machine learning classifier to partition CMM using hybrid mesh segmentation is proposed and implemented by Hase et al. [22]. A detailed description of automating threshold prediction is beyond the scope of this chapter.

11.3.2 Hybrid Mesh Segmentation

The objective of hybrid mesh segmentation is to partition CMM into basic primitives like a plane, sphere, cylinder, cone and torus. It is difficult to segment CMM by using facet-based region growing or vertex-based region growing alone. Vertex-based region growing technique is used to detect curved surface whereas facet-based growing technique is used to detect curved features and planes. None of these techniques on their own gives a robust solution to recognize feature from CMM, a promising approach wherein intelligent blending of facet-based, vertex-based, rule-based reasoning are combined.

Hybrid mesh segmentation uses the "Facet Area" property to group facets together, using a combination of vertex-based and facet-based region growing algorithms [23]. It uses region growing algorithms to cluster facets into groups. After segmentation, shape primitives detection has been carried out wherein each facet group is subjected to several conformal tests to identify the type of analytical surfaces such as a cylinder, cone, sphere, or tori. After extraction of analytical surfaces, feature boundaries are identified.

11.3.2.1 Iterative Region Merging

The hybrid mesh segmentation leads to over-segmentation. The over-segmented regions are needed to be merged again to generate the single region. The proposed iterative region merging technique is based on predefined merging criteria. It repeatedly merges the regions that have similar geometric property. Following steps has been carried out in iterative region merging.

11.3.2.2 Region Merging

A single pass is not enough to merge all features. Only if two features are adjacent, they will be merged to one on satisfying geometry equality test. After merging, adjacency may be changed, so features that were not eligible for merging in the previous pass will be merged in next pass.

11.3.2.3 Reclamation

After region merging, small cracks are observed close to the corner and at the region boundaries [24]. To make a watertight model, these uncollected facets are reclaimed into the adjacent identified regions (Feature) based on reclamation criteria.

Figure 11.4 illustrates the cylindrical regions generated by the hybrid mesh segmentation, Fig. 11.3a shows the original mesh models, Fig. 11.4a demonstrates the segmentation results (12 planes and 523 cylindrical patches), Fig. 11.4b demon-

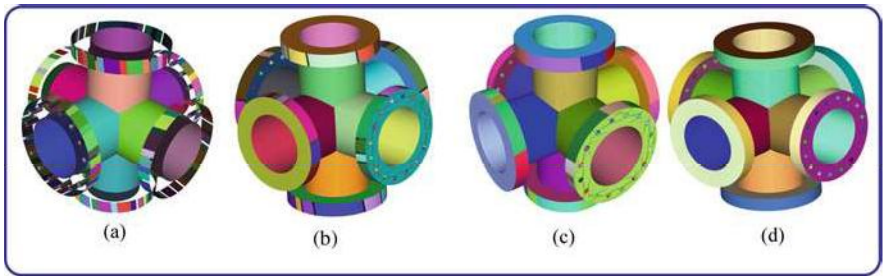

Fig. 11.4 Hybrid mesh segmentation process. (**a**) Segmentation. (**b**) Region merging. (**c**) Reclamation. (**d**) Region merging after reclamation

Table 11.1 A quantitative comparison of CAD mesh model

Test cases	F	V	S	Adf	N_{Rbrm}	N_{Rarm}	T	C
Figure 11.5a	1640	812	0.417	0.8	39	20	0.211	100
Figure 11.5c	2472	1230	0.624	0.6	55	29	0.864	99.67
Figure 11.5e	38,932	19,092	9.84	0.7	1169	630	4.257	99.58
Figure 11.5g	1380	690	0.349	0.75	36	25	0.254	99.28
Figure 11.5i	12,068	6034	2.23	0.75	158	69	1.078	100
Figure 11.5k	528	264	0.134	0.75	21	11	0.121	100

F: number of facets, V: number of vertex, S: STL size (in MB), Adf: predicted area deviation factor, C: % coverage, T: overall timing (in a second), N_{Rbrm}: number of regions before region merging, N_{Rarm}: number of regions after region merging

strates the region is merging results, Fig. 11.4c demonstrates the reclamation results, and Fig. 11.4d illustrates the final region merging after reclamation (12 planes and 50 cylinders). The system takes approximately 1.759 s for feature detection.

11.4 Volumetric Feature Recognition

The volumetric features like holes and blends are detected by applying a set of rules based on adjacency information of the primitives noticed in the previous step. Most of the existing approaches evaluate pockets, slots, etc. However, 60% of the average portion of the total facets in CAD mesh model are blended features [25], and holes constitute a significant percentage of features in mechanical engineering parts. Hence, we considered blends and hole recognition.

To test the efficacy of propose algorithm to recognize volumetric features, the benchmark test cases from repository have been used. These test cases have either complex interacting features or the features are in large in number. Using random color for different primitives, features can be interpreted.

Table 11.1 summarizes the performance measure for a proposed algorithm for the test cases shown in Fig. 11.5a, c, e, g, i, k. We used percentage coverage as a

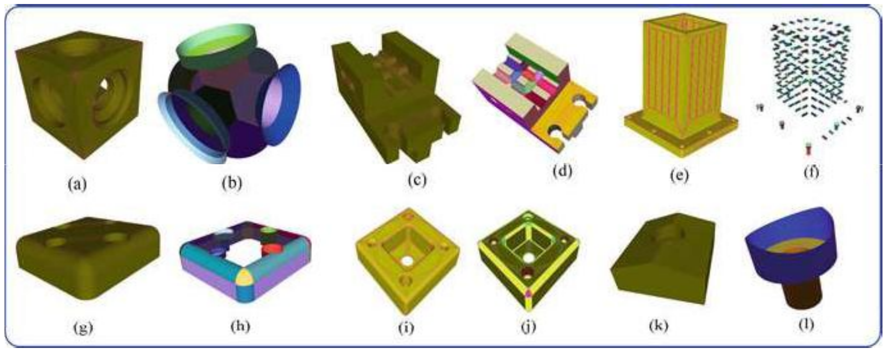

Fig. 11.5 Illustrates the interacting feature recognition of a model. (**a**) Test case 1. (**b**) Output of test case 1. (**c**) Good die. (**d**) Output of good die. (**e**) Tooling block. (**f**) Features of tooling block. (**g**) Text case 2. (**h**) Output for test case 2. (**i**) Test case 3. (**j**) Output of test case 3. (**k**) Test case 4. (**l**) Features of test case 4

measure of an indicator for successful segmentation. It is a ratio of a number of features recognized to actual the number of features present in a CAD mesh model.

11.5 Results and Discussion

11.5.1 Comparison with a Recently Developed Algorithm

The comparison of the propose technique is made with existing state-of-the-art approaches like RANSAC [11], Attene et al. [10], and Li et al. [12] where source code is publicly available. The results for Le and Duan [14] are taken from [14] as the source code was not available. The proposed approach does not depend on attributes like curvature, minimum feature dimension, number of clusters, number of cutting planes, the orientation of model, and thickness of the slice to extract volumetric features.

Table 11.2 summarizes the quantitative comparison for a proposed algorithm for the benchmark test cases. Quantitative evaluation has been carried out using a number of primitives, the coverage percentage, and the distance error. As noted in Fig. 11.6, the proposed algorithm yields better results than RANSAC [11] and Attene et al. [10]. The results revealed that the proposed technique is comparable to Le and Duan [14].

Table 11.2 Quantitative evaluation of primitive quality test cases shown in Fig. 11.6

Model name	Number of primitives					Coverage (%)					Distance error ($\times 10^{-3}$)				
	I	II	III	IV	V	I	II	III	IV	V	I	II	III	IV	V
Block	**14**	14	14	9	14	**100**	100	100	64.3	99	**0.04**	0.37	0.08	n/a	0.69
Cover rear	**45**	28	45	45	28	**100**	87.8	100	100	87.8	**0.02**	0.11	0.04	n/a	0.15
Pump carter	**83**	57	63	76	57	**99.5**	92.9	98.6	99.2	92.9	**0.03**	0.16	0.3	n/a	2.3
Stator	**12**	12	12	6	n/a	**100**	100	100	50	n/a	**0.01**	0.8	0.47	n/a	n/a

I: Proposed algorithm, II: RANSAC [11], III: Le and Duan [14], IV: Attene et al. [10], V: GlobFit [12]

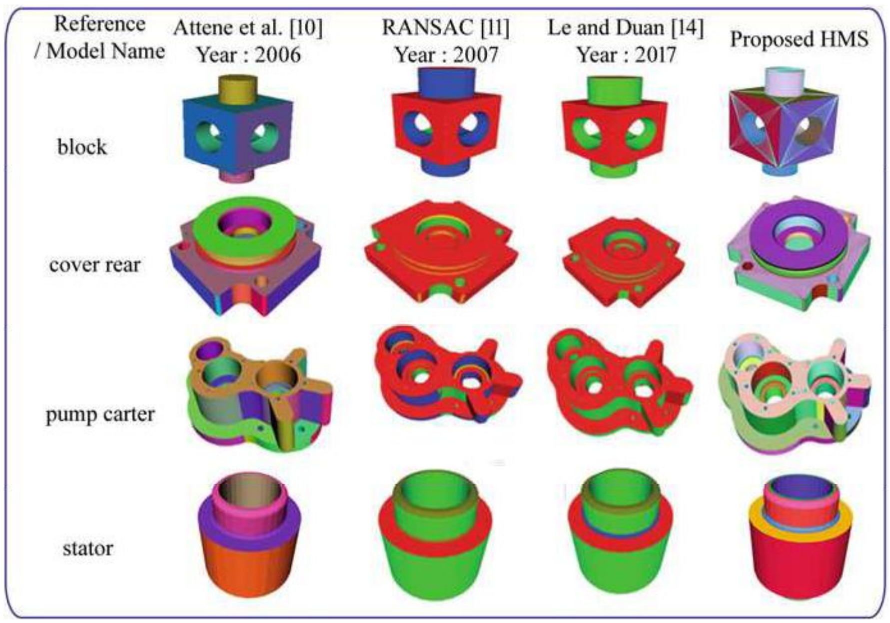

Fig. 11.6 Comparison with the existing algorithm

11.6 Conclusion

In this research, an elegant method has been proposed and implemented for extracting volumetric features from CMM using a hybrid region growing approach. The rule-based reasoning approach for feature recognition has been used. The proposed algorithm captures and separates intersecting features as well.

Comparing with existing recent approaches such as Attene et al. [10], RANSAC [11], Adhikary et al. [13], Le and Duan [14], Muraleedharan et al. [20], and other benchmark test cases, the proposed technique successfully recognized the features such as blends, compound holes and their interactions and found to be robust and consistent with coverage of more than 95% in addressing volumetric features. The proposed approach is simple, general, and more reliable.

The future work could be aimed at capturing the parent-child relationship of extracted features and threshold prediction using various methods such as deep learning, machine learning for automatic segmentation.

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References

1. D. Yan, W. Wang, Y. Liu, Z. Yang, Variational mesh segmentation via quadric surface fitting. Comput. Aided Des. **44**(11), 1072–1082 (2012)
2. S. Xú, N. Anwer, C. Mehdi-Souzani, R. Harik, L. Qiao, STEP-NC based reverse engineering of in-process model of NC simulation. Int. J. Adv. Manuf. Technol. **86**(9–12), 3267–3288 (2016)
3. T. Várady, M. Facello, Z. Terék, Automatic extraction of surface structures in digital shape reconstruction. Comput. Aided Des. **39**(5), 379–388 (2007)
4. P. Benkő, T. Várady, Segmentation methods for smooth point regions of conventional engineering objects. Comput. Aided Des. **36**(6), 511–523 (2004)
5. D. Tang, L. Zheng, Z. Li, An intelligent feature-based design for stamping system. Int. J. Adv. Manuf. Technol. **18**(3), 193–200 (2001)
6. J. Corney, C. Hayes, V. Sundararajan, P. Wright, The CAD/CAM interface: a 25-year retrospective. J. Comput. Inf. Sci. Eng. **5**(3), 188–197 (2005)
7. M. Hayasi, B. Asiabanpour, Extraction of manufacturing information from design-by-feature solid model through feature recognition. Int. J. Adv. Manuf. Technol. **44**(11–12), 1191–1203 (2009)
8. F. Bianconi, Bridging the gap between CAD and CAE using STL files. Int. J. CAD/CAM **2**(1), 55–67 (2002)
9. V. Sunil, S. Pande, Automatic recognition of features from freeform surface CAD models. Comput. Aided Des. **40**(4), 502–517 (2008)
10. M. Attene, B. Falcidieno, M. Spagnuolo, Hierarchical mesh segmentation based on fitting primitives. Vis. Comput. **22**(3), 181–193 (2006)
11. R. Schnabel, R. Wahl, R. Klein, Efficient RANSAC for point-cloud shape detection. Comput. Graph. Forum **26**(2), 214–226 (2007)
12. Y. Li, X. Wu, Y. Chrysathou, A. Sharf, D. Cohen-Or, N. Mitra, GlobFit: consistently fitting primitives by discovering global relations. ACM Trans. Graph. **30**(4), 52, 12 (2011)
13. N. Adhikary, B. Gurumoorthy, A slice based approach to recognize and extract free-form volumetric features in a CAD mesh model. Comput. Aided Des. Appl. **13**(5), 587–599 (2016)
14. T. Le, Y. Duan, A primitive-based 3D segmentation algorithm for mechanical CAD models. Comput. Aided Geom. Des. **52–53**, 231–246 (2017)
15. J. Shah, D. Anderson, Y.S. Kim, S. Joshi, A discourse on geometric feature recognition from CAD models. J. Comput. Inf. Sci. Eng. **1**(1), 41–51 (2001)
16. B. Babic, N. Nesic, Z. Miljkovic, A review of automated feature recognition with rule-based pattern recognition. Comput. Ind. **59**(4), 321–337 (2008)

17. A. Verma, S. Rajotia, A review of machining feature recognition methodologies. Int. J. Comput. Integr. Manuf. **23**(4), 353–368 (2010)
18. R. Zbiciak, C. Grabowik, Feature recognition methods review, in *Proceedings of the 13th International Scientific Conference. RESRB 2016. Lecture Notes in Mechanical Engineering*, ed. by E. Rusiński, D. Pietrusiak, (Springer, Cham, 2017), pp. 605–615. https://doi.org/10.1007/978-3-319-50938-9_63
19. D. Xiao, H. Lin, C. Xian, S. Gao, CAD mesh model segmentation by clustering. Comput. Graph. **35**(3), 685–691 (2011)
20. L. Muraleedharan, S. Kannan, A. Karve, R. Muthuganapathy, Random cutting plane approach for identifying volumetric features in a CAD mesh model. Comput. Graph. **70**, 51–61 (2018)
21. A. Agathos, I. Pratikakis, S. Perantonis, N. Sapidis, P. Azariadis, 3D mesh segmentation methodologies for CAD applications. Comput. Aided Des. Appl. **4**(6), 827–841 (2007)
22. V. Hase, Y. Bhalerao, G.J. Vikhe Patil, M.P. Nagarkar, in *Proceedings of the ICCET 2019 4th International Conference on Computing in Engineering and Technology. ICCET 2019*, (AISC Series of Springer, 2019), ed. by B. Iyer, P. S. Deshpande, S. C. Sharma, U. Shiurkar, (2019)
23. V. Hase, Y. Bhalerao, S. Verma, S. Jadhav, G. Vikhe Patil, Complex hole recognition from CAD mesh models. Int. J. Manage. Technol. Eng. **8**(IX), 1102–1119 (2018)
24. H. Kim, H. Choi, K. Lee, Feature detection of triangular meshes based on tensor voting theory. Comput. Aided Des. **41**(1), 47–58 (2009)
25. N. Rafibakhsh, M. Campbell, Hierarchical fuzzy primitive surface classification from tessellated solids for defining part-to-part removal directions. J. Comput. Inf. Sci. Eng. **18**(1), 011006 (2017)