Intelligent systems for volumetric feature recognition from CAD mesh models

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Abstract: This paper presents an intelligent technique to recognise the volumetric features from CAD mesh models based on hybrid mesh segmentation. The hybrid approach is an intelligent blending of facet-based, vertex based, rule-based, and artificial neural network (ANN)-based techniques. Comparing with existing state-of-the-art approaches, 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. ANN-based intelligent threshold prediction makes hybrid mesh segmentation automatic. The proposed technique automatically extracts volumetric features like blends and intersecting holes along with their geometric parameters. The proposed approach has been extensively tested on various benchmark test cases. The proposed approach outperforms the existing techniques favourably and found to be robust and consistent with coverage of more than 95% in addressing volumetric features.

Keywords: CAD mesh model; CMM; hybrid mesh segmentation; volumetric feature recognition.

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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. Recognising 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 paper is the CMM.

Segmentation aims to partition CMM into 'meaningful' regions (Yan et al., 2012). Each region can be fitted to a distinct, mathematically analyzable form (Xú et al., 2016). Literature reveals the availability of many mesh segmentation algorithms. However, most of them are not suitable for CMM as scan derived mesh are 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 (Xú et al., 2016). It is difficult to establish one global threshold, and so several mesh segmentation methods set local threshold while computing curvature (Benkő and Várady, 2004; Várady et al., 2007).

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 (Tang et al., 2001; Corney et al., 2005). Therefore a need is exists to develop FR from the mesh model.

Standard triangulated language (STL) is globally accepted by all CAD/CAM system which makes it platform-independent data exchange format (Hayasi and Asiabanpour, 2009). If we recognise features from STL model, it will be a unique data translator service (Bianconi, 2002; Sunil and Pande, 2008).

Above observations have inspired the research work reported in this paper. The hybrid mesh segmentation approach is used for detecting volumetric features. The proposed algorithm segments the CMM into basic primitives like a plane, cylinder, cone, sphere, 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. (2006), Schnabel et al. (2007), Li et al. (2011), Yan et al. (2012), Adhikary and Gurumoorthy (2016), and Le and Duan (2017).

The proposed approach has the following contributions:

- 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.

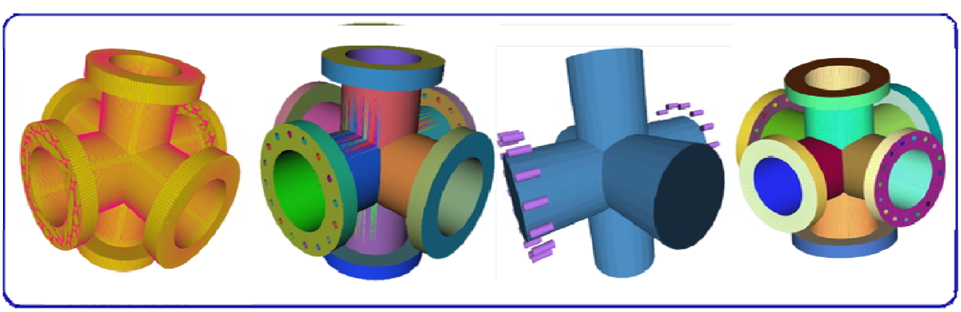
The rest of this paper is organised as follows: Section 2 provides a comprehensive review of relevant literature; Section 3 illustrates a proposed methodology for the volumetric feature recognition; Section 4 deals with volumetric feature recognition; Section 5 provides a quantitative comparison with a recently developed algorithm; Section 6 present conclusion and future scope.

2 Literature review

A comprehensive review of various FR approaches with their strengths and weaknesses are reviewed in the literature (Shah et al., 2001; Corney et al., 2005; Babic et al., 2008; Sunil and Pande, 2008; Verma and Rajotia, 2010; Xiao et al., 2011; Zbiciak and Grabowik, 2017; Di Angelo et al., 2018). The focus of the current research work is to compare the robustness and consistency of the 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. (2006) designed a hierarchical fitting primitives technique of mesh segmentation which needs a number of clusters as an input criterion along with visual inspection to carry out segmentation. However, knowing a number of clusters before feature extraction is difficult. Figures 1(b) and 2(b) shows the failure cases of Attene et al. (2006).

Figure 1 Failure cases for intersecting volumetric feature, (a) input CAD mesh model (b) Attene et al. (2006) (c) Muraleedharan et al. (2018) (d) output (see online version for colours)



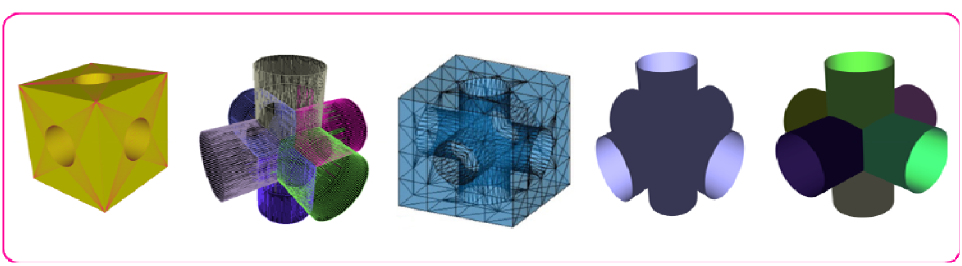
(a) (b) (c) (d)

Schnabel et al. (2007) designed random sample consensus (RANSAC)-based framework for recognising basic primitives. However, the approach either over segment or under segments the model. It results in inaccuracy of feature extraction. Li et al. (2011) modified the approach of Schnabel et al. (2007) 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 output. Yan et al. (2012) 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 (2016) presented an algorithm to recognise 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 Figure 2(a). Their algorithm depends on the choice of minimum feature dimension (MFD) and must be known in advance before feature extraction. Figure 2(c) shows the failure case of Adhikary and Gurumoorthy (2016).

Muraleedharan et al. (2018) 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 1(c) shows the limitation of their approach. They used Gaussian curvature for boundary extraction and separates 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. Figure 1(c) and 2(d) shows examples of volumetric feature recognition but unable to separate into individual features. As feature joints have a complex boundary, segmentation unable to separate them. However, the proposed algorithm detects intersecting features along with geometric parameters.

Figure 2 Failure cases for interacting features, (a) input CAD mesh model (b) Attene et al. (2006) (c) Adhikary and Gurumoorthy (2016) (d) Muraleedharan et al. (2018) (e) output (see online version for colours)



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

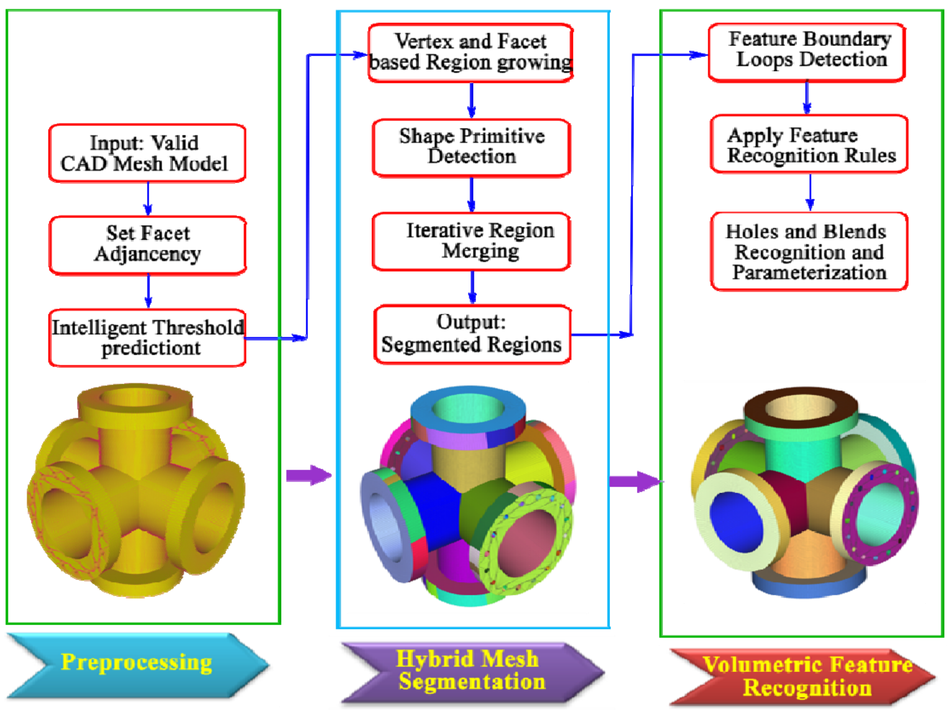
Le and Duan (2017) used uniform slicing along the major direction. They used a dimensional reduction technique which transforms 3D primitives to 2D in order to get a profile curve. The primitives are detected based on profile curve analysis. However, the algorithm is slice thickness dependent, and slicing techniques fail to detect or separate complex interacting features as noted by Adhikary and Gurumoorthy (2016).

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 1(d) and 2(e) shows examples of volumetric feature recognition. Hybrid mesh segmentation recognised all the features whereas the closest one among others is the Le and Duan (2017).

3 Methodology

The proposed algorithm involves three steps viz. preprocessing, hybrid mesh segmentation and volumetric feature recognition. Figure 3 illustrates the overall strategy to extract volumetric features from CMM which consists of the following steps:

Figure 3 The framework of the proposed methodology (see online version for colours)



3.1 Preprocessing

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

Input CAD mesh model

In this research work, a valid STL model which is free from errors is taken as input in American Standard Code for Information Interchange (ASCII) or binary format, hence no need of model healing (Sunil and Pande, 2008).

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 threshold at the beginning. It is a cumbersome task of finding a threshold value for getting the expected results. Most of the time, a trial and error approach is used to identify a correct threshold (Muraleedharan et al., 2018). 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 (Agathos et al., 2007). 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 great importance.

As stated above, area deviation factor (threshold) is the decisive factor in segmentation quality. Intelligent prediction of threshold using the artificial neural network (ANN) to partition CMM using hybrid mesh segmentation is proposed and implemented by Hase et al. (2019). A detailed description of intelligent threshold prediction is beyond the scope of this paper.

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 tori. 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 recognise 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 (Hase et al., 2018). It uses region growing algorithms to cluster facets into groups. After segmentation, shape primitive 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.

Iterative region merging

The Hybrid mesh segmentation leads to over-segmentation. The over segmented regions are need 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.

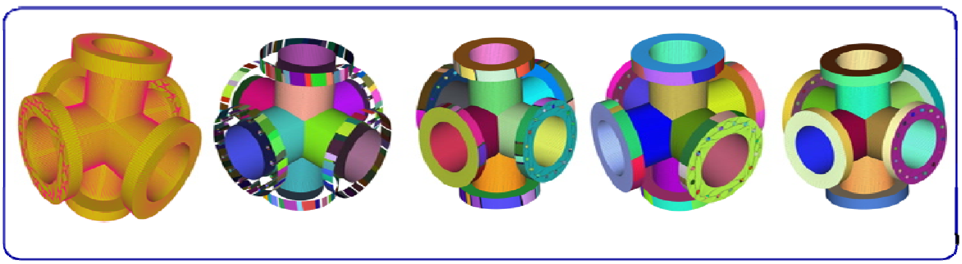
Region merging

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.

Reclamation

After region merging, small cracks are observed close to the corner and at the region boundaries (Kim et al., 2009). To make a watertight model, these uncollected facets are reclaimed into the adjacent identified regions (feature) based on reclamation criteria.

Figure 4 Hybrid mesh segmentation process, (a) input CAD mesh model (b) segmentation (c) region merging (d) reclamation (e) region merging after reclamation (see online version for colours)



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

Figure 4 illustrates the cylindrical regions generated by the hybrid mesh segmentation, Figure 4(a) shows the input CAD mesh models, Figure 4(b) demonstrates the segmentation results (12 planes and 523 cylindrical patches), Figure 4(c) demonstrates the region merging results, Figure 4(d) demonstrates the reclamation results and Figure 4(e) illustrates the final region merging after reclamation (12 planes and 50 cylinders). The system takes approximately 1.759 seconds for feature detection.

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 is of blends features, and holes constitute a significant percentage of features in mechanical engineering parts (Rafibakhsh and Campbell, 2018). Hence, we considered blends and hole recognition.

To test the efficacy of algorithms to recognise 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 colour for different primitives, features can be interpreted.

Figures 5(a) and 5(c) shows volumetric interacting features. The techniques proposed by Muraleedharan et al. (2018) and Adhikary and Gurumoorthy (2016) are unable to separate individual features. On the other hand, the proposed approach using hybrid mesh segmentation is able to extract the interacting features along with their geometric parameters. For the model 'tooling block' shown in Figure 5(e) taken from benchmark has 630 volumetric features. The proposed techniques demonstrate efficacy by extracting all the 630 features in just 4.257 seconds as shown in Figure 5(f). The model shown in Figure 5(g) has complex interacting features wherein blends interact with holes. The proposed approach has the ability to extract and separates complex interacting features along with their geometric parameters. Figure 5(i) shows the model with complex nested feature interaction. The proposed approach is successful in extracting such complex holes along their parameters. As the proposed algorithm extracts features without edge detection, the complex hole lying on multiple planer regions are detected and separated successfully as shown in Figure 5(k).

Figure 5 Illustration of the interacting feature recognition of a model, (a) test case1 (b) feature of test case1 (c) good die (d) features of good die (e) tooling block (f) features of tooling block (g) test case2 (h) features of test case2 (i) test case3 (j) features of test case3 (k) test case4 (l) features of test case4 (see online version for colours)

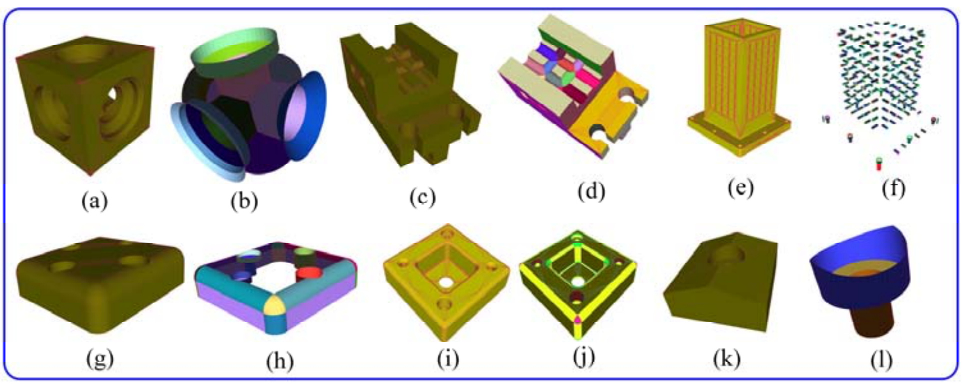


Table 1 summarises the performance measure for a proposed algorithm for the test cases shown in Figures 5(a), 5(c), 5(e), 5(g), 5(i), and 5(k). We used percentage coverage as a measure of an indicator for successful segmentation. The coverage is a ratio of a number of features recognised to actual the number of features present in a CAD mesh model. For all the benchmark test cases, percentage coverage is very high.

Table 1 A quantitative comparison of CAD mesh models

Test cases	*F*	*V*	*S*	*Adf*	N_{Rbrm}	N_{Rarm}	*T*	*C*
Figure 5(a)	1,640	812	0.417	0.80	39	20	0.211	100
Figure 5(c)	2,472	1,230	0.624	0.60	55	29	0.864	99.67
Figure 5(e)	38,932	19,092	9.84	0.70	1169	630	4.257	99.58
Figure 5(g)	1,380	690	0.349	0.75	36	25	0.254	99.28
Figure 5(i)	12,068	6,034	2.23	0.75	158	69	1.078	100
Figure 5(k)	528	264	0.134	0.75	21	11	0.121	100

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

5 Results and discussion

5.1 Comparison with a recently developed algorithm

The comparison of the proposed technique is made with existing state-of-the-art approaches like Attene et al. (2006), RANSAC, Li et al. (2011) where source code is publicly available. The results for Le and Duan (2017) are taken from Le and Duan (2017) as the source code was not available. The proposed approach does not depend on attributes like curvature, MFD, number of clusters, number of cutting planes, the orientation of model and thickness of the slice to extract volumetric features.

Figure 6 Comparison with the existing algorithm (see online version for colours)

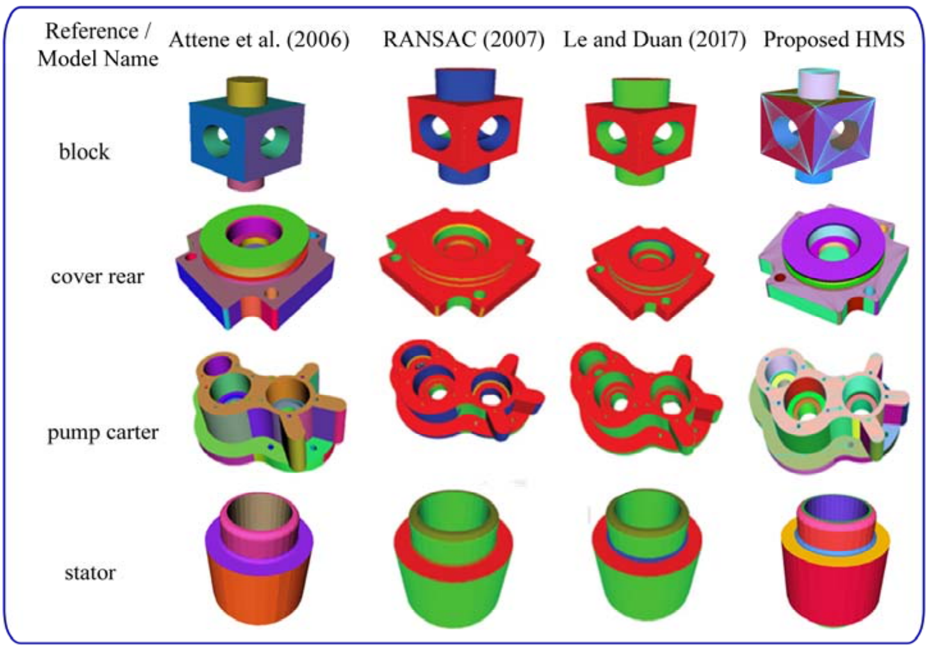


Table 2 Quantitative evaluation of primitive quality for test cases shown in Figure 6

Model name	*Number of primitives*					*Coverage (%)*					*Distance error (× 10^{-3})*				
	I	*II*	*III*	*IV*	*V*	*I*	*II*	*III*	*IV*	*V*	*I*	*II*	*III*	*IV*	*V*
Block	*14*	9	14	14	14	*100*	64.28	99.98	98.98	99.98	*0.04*	n/a	0.37	0.69	0.08
Cover rear	*45*	45	28	28	45	*100*	100	87.79	87.79	100	*0.02*	n/a	0.11	0.15	0.04
Pump carter	*83*	76	57	57	63	*99.45*	99.15	92.87	92.87	98.61	*0.03*	n/a	0.16	2.3	0.3
Stator	*12*	6	12	n/a	12	*100*	50	99.99	n/a	100	*0.01*	n/a	0.8	n/a	0.47

Notes: (I): HMS; (II): Attene et al. (2006); (III): RANSAC; (IV): GlobFit; (V): Le and Duan (2017).

Table 2 summarises the quantitative comparison for a proposed algorithm for the benchmark test cases. Quantitative evaluation has been carried out by computing percentage coverage based on actual a number of primitives presents in a model along with the distance error. As noted in Figure 6, the proposed algorithm yields better results than RANSAC and Attene et al. (2006). The results revealed that the proposed technique is comparable to Le and Duan (2017).

6 Conclusions

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 state-of-the-art approaches and other benchmark test cases, the proposed technique successfully recognised 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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