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Manufacturability analysis for additive manufacturing using a novel feature recognition technique

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ABSTRACT
Additive Manufacturing (AM) increases much design freedom for designers to conceive complex parts. However, the increased complexity makes the manufacturability analysis difficult for the designed parts when applying traditional methods. To solve this problem, this paper introduces a new feature-based method for manufacturability analysis in AM by using Heat Kernel Signature. This method can both identify geometric features and manufacturing constrains which are defined in this paper for comprehensive analysis from the perspective of manufacturing to support the redesign and downstream process planning. A couple of example part models including a standard testing part for AM are used to demonstrate the feasibility of applying the proposed method for feature recognition and manufacturability analysis.

KEYWORDS
Manufacturability analysis; feature recognition; heat kernel signature; additive manufacturing

1. Introduction

By processing materials in a layer by layer approach, the additive manufacturing (AM) process is useful for testing and prototyping or obtaining end-use products. This breakthrough in manufacturing technology makes the fabrication of complex shapes and intricate geometrical features possible and has the potential to significantly simplify the production of complex solid models directly from CAD data. It provides designers not only the freedom to their unruly imagination, but it also allows distributed and decentralized manufacturing and it is easier than tradition manufacturing to be run. Therefore, additive manufacturing technology is introduced to various fields such as industrial, scientific, education, medical [1], archaeological [19], artistic [20] or daily use.

The widespread development of additive manufacturing is also accompanied with an erroneous impression among non-experts that any model that can be designed in a CAD program can be fabricated using a 3D printer. However, although AM expands the geometric design space compared with conventional manufacturing, but it does not remove all manufacturing restrictions. Designers might be unaware of specific manufacturing restrictions or rules of additive manufacturing processes, which sometimes would cause 'non-manufacturable' designs. This is a popular problem, which can be time-consuming and therefore costly, especially in cases where the designs were accomplished without professional design-for-additive-manufacturing training. In order to minimize these type of problems and reduce the time consumption of design, an automated manufacturability analysis (MA) system is needed to provide designers with a preliminary tool classifying, based on available resources, their designs into manufacturable or unmanufacturable domains. Automated manufacturability analysis system for traditional processing technology started to develop rapidly since 1990s [10] and significant efforts have been made to integrate it into CAD/CAM/CAPP system such as UGS, PTC and Dassault [8]. To aid with this, various manufacturability analysis or Design for Manufacturing methodologies have been developed including: neural network, fuzzy logic, agent-based systems, rule-based systems, object oriented techniques, analytical hierarchy processes and case-based reasoning.

Along with the robust development of additive manufacturing technology, there have been many guidelines and research for the topic of Design for Additive manufacturing. However, hardly any attempt has been made to automated manufacturability analysis systems for additive manufacturing. Existing software to analyze design models and generate input files for 3D printer mostly accompany a specific printer and intent to implement model cleanup, build direction optimization, and tool

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path generation [11]. Although these software suites are able to deal with some types of geometric errors such as duplicate vertices, self-intersections, none of these tools can identify specific problems of solid models due to these feature restrictions.

In this paper, we propose a novel feature-based method for manufacturability analysis in AM by using Heat Kernel Signature to recognize the detailed information of design features. The paper is organized as follows: A brief introduction of the manufacturability problems with AM is given at the beginning; then, detailed descriptions of MA of traditional processing and AM is presented; next, related research about feature recognition is reviewed; followed by the overall proposed methodology in a step by step manner, and several example models are used to demonstrate effectiveness of our method to some key features; Finally, some closing remarks are made in the conclusion.

2. Background and literature review

Feature recognition is a critical sub-discipline of CAD/CAM that focuses on the design and implementation of algorithms for detecting manufacturing information from the three-dimensional solid models produced by CAD systems [4]. These three-dimensional solid models provide the geometric and topological information of a component; however, it is not sufficient for the manufacturability analysis. To achieve this, the solid models need to be interpreted in terms of appropriate predefined features. Protrusions, holes, slots, pockets, ribs, bosses and grooves are typical examples of the features. The proposed method for such system is shown in Figure 1.

Generally, features are characteristics of functional interests on an object. According to different interests, they can be assigned to different disciplines. For designers, the features in solid models describe how the part is conceived. For machinists, the features should be able to capture how the part is processed. Although these two methods are both based on topologic and geometric reasoning, it is difficult to translate CAD models into the manufacturing requirements. To connect design intent and manufacturing features, there are mainly two approaches: feature recognition and feature-based design [16]. Compared with the feature recognition, feature-based design has drawbacks such as design constraints and complexity. For example, the most used design features are not manufacturing features. Meanwhile, considering the more and more powerful computers, feature recognition can be a general solution to the interface between design and manufacturing.

2.1. Related research/literature

Automatic feature recognition has been an active research area for decades. Many different techniques have been proposed. The basic problem that feature recognition technology tries to solve is identifying high-level information from the low-level geometric entities [11], such as a collection of faces, edges, vertices and the connectivity relationships in a CAD model and interpreting such high-level hints as a set of features.

Many researchers have adopted various approaches based on different principles and design models evolved in the recognition process. However, their methods do not provide a perfect solution to the problems in this area. They are facing various criticisms including their lack of practicability, incomplete topology or geometry information, inefficiency in dealing with interacting features and limitations in applicability to sets of simple features. A brief review of some feature recognition methods is provided here to clarify the difference and limitations of present works.

- Graph matching method: In the graph matching algorithm [13], the boundary elements of a part is represented into a graph data structure, then the graph can be matched with templates of particular feature patterns. Graph matching method is efficient due to the graph interpretation, however, it has difficulties on dealing with intersecting features and may be computationally expensive [4].
- Volume decomposition approach: The volumetric decomposition approach decomposes the removal volume of solid model into a set of cells which can be aggregated into machining features [4]. Although it is effective in handling intersecting features due to loss of topological and geometric information, it still has computational problems stemming from the large number of possible combinations of different features [7].
- Rule-based approach: The rule-based approach is based on the presence rule that a feature should contribute a minimal indispensable boundary to the part. Later it was further developed by defining various rules of interpretations of features [4]. However, it is not a practical approach for feature recognition, because it lacks geometric and topological information, which is necessary for tool path planning, and the massive amount of possible interpretations are difficult to be standardized. Rebuilding new sets of rules is often necessary for even a slight change of part [18].
- Neural network-based method: An artificial neural network can handle the features having variable

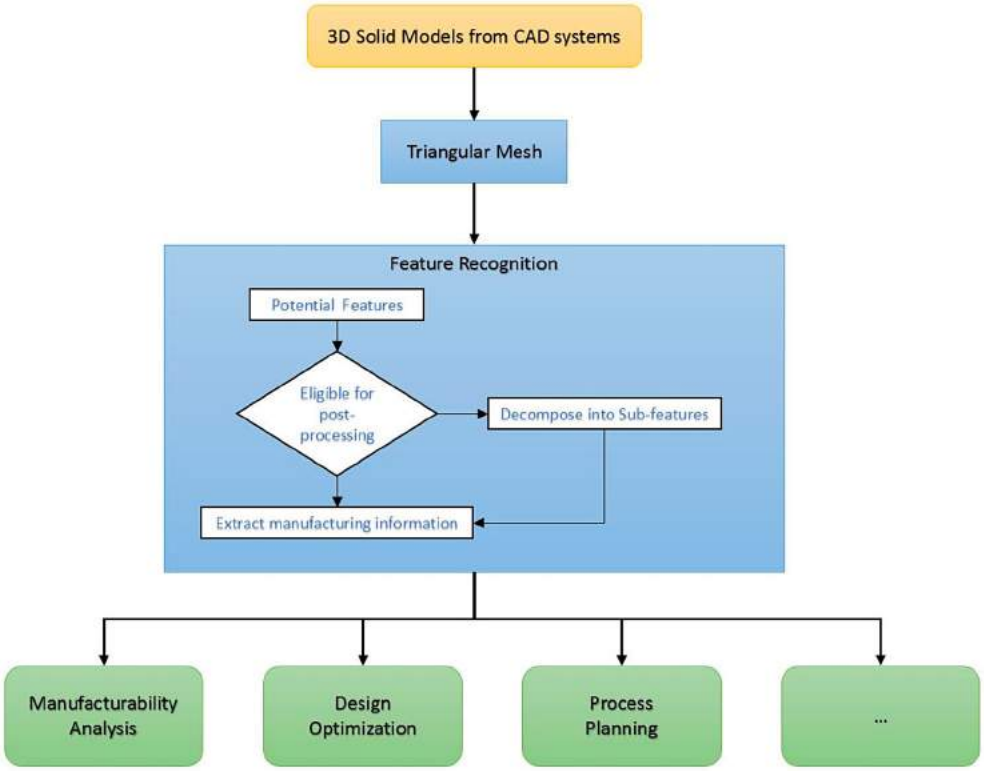

Figure 1. Flowchart of the proposed feature recognition system.

topology by using its generalization and learning ability [15, 20]. However, a neural network has to be trained with sufficient input vectors for each type of feature. If a new feature comes up, it has to be retrained and retested [7].

– Hybrid approaches: Taking advantage of multiple recognition methods, researchers combined different above feature recognition techniques to overcome some of their limitations. For example, rule-based approach, neural network and volume decomposition approach can be combined to solve the interacting machining features [17]. Volume decomposition and graph machining method can be combined to identify manufacturing features from solid model data [21]. However, hybrid approaches may still have limitations, such as limitations to certain types of features, or their inability to differentiate non-orthogonal shapes.

In general, feature recognition technologies are facing three main difficulties, defined as follows [17]: computational complexity, domain of predefined features and manufacturing information. The feature interaction and non-orthogonal features make the interpretations of recognized features quite complicate. Meanwhile, the massive amount of possible interpretations causes algorithm complexity and expensive computation. To overcome this problem, the cost is the limitation of recognizable features or loss of topological and geometric information. Therefore, the recognized features by some approach don't have enough information to facilitate the manufacturing analysis.

In this way, an ideal feature recognition system should be able to recognize all kinds of features with practical computation and provide sufficient manufacturing information for post-processing, such as manufacturing analysis, design optimization and downstream production plan. In this paper, we introduce a new approach of feature recognition based on heat kernel signature. Using a mesh file input, it has the ability to recognize all kinds of potential features and still keep the information about vertex, surfaces and volumes. The work presented is thus in the early stages of this system. To be a complete solution to manufacturing support, a lot of work need to be done for designing algorithm to analyzing the manufacturing information.

2.2. Feature representations

In the previous works, the application domain of feature recognition that received most attention is machining process. As shown in Figure 2, a feature for machining can be typically defined into two categories [4]:

1. Surface feature: a surface feature is a collection of boundary faces that can be created by machining operations. It is represented by a graph structure including the faces and their connecting edges.
2. Volumetric feature: a volumetric feature is a removal volume swept by the cutting surfaces of machining process. It can be represented by the vertices, feature type, and feature volume augmented with surfaces.

Obviously, volumetric feature is a more informative representation of the machining process than surface feature. From the additive manufacturing point of view, volumetric feature is still an effective method to define the manufacturing feature. But due to the opposite way of dealing with the material, the manufacturing feature for AM needs to be defined as the volume created or added by manufacturing process instead of removed. As shown in Figure 8 and 9, the NIST test part is a great example of volumetric feature representation for AM.

To be applicable to manufacturability analysis, manufacturing feature needs geometric information that can be used to parameterize the manufacturing operations. In our method, we use 3D triangular mesh as input. It comprises the vertex coordinates and edge connections of a set of triangles. After the feature recognition process, we would know which face the vertices belong to, and which feature the faces belong to. Then by analyzing the relative positions of these vertices, we can find the attributes of features, such as diameter, length, height, distance, area and volume. Thereafter, manufacturability analysis is based on the preset rules to this geometric dimensioning.

Comparing to subtractive process, due to the gravity and layer-by-layer mechanism, one of the most obvious characteristic of manufacturability analysis for AM is that its constraints don't include the tool approach direction and tool accessibility. Therefore, there is a reduced need to define feature into different types based on shape. In this paper, all protrusions and pocket features are regarded as potential features, and after successful separation into one of these two, the geometrical constraints defined in section 3.2 will be examined.

3. Manufacturability analysis

Manufacturability is defined as a property of a design that dictates whether or not the design can be validated in a given production environment. Manufacturability analysis is a process which involves analyzing the design for potential manufacturability problems and estimating its manufacturing cost [10]. It may be regarded as a well-defined and specific subset of system engineering principles [2]. In a given condition of design and manufacturing resource, the traditional manufacturability analysis can be detailed into following steps [10]:

1. Determine whether the design is manufacturable or not
2. If the design is manufacturable, then determine its manufacturability evaluation and compare with other solutions
3. If the design is not manufacturable, then identify which design feature has manufacturability issues.

It is evident that whether the manufacturability of a design is mostly determined by the geometric constrains imposed by manufacturing processes, and the purpose of manufacturability analysis is to minimize constraint violations in design [3]. Also, it is important to note that manufacturability criteria are flexible and depend on different given production conditions. Detailing the first step of manufacturability analysis is the focus of this paper.

3.1. Traditional manufacturability analysis

Traditionally, manufacturability is one of the key aspects in product development to reduce the costs and time and ensure product competitiveness in the market. The translation of a conceptual design into a final product needs to be accomplished by repetitive iterations between design and manufacturability analysis of the product development life cycle [10]. The designer uses experience and prototyping iterations to modify or redesign the products. Usually products and manufacturing systems are extremely complex and tough on a wide variety of challenging research issue, it is nearly impossible for a single designer to master all facets and their internal relationships. Therefore, an automated manufacturability analysis system can greatly improve the human weakness and expedite the iterations in the product development process.

The development and implementation of manufacturability analysis system has been progressing rapidly over the last decades. For example, a manufacturability analysis system for milling and drilling process described four basic rules for machining features [6]:

1. Non-intrusion: Design feature should be producible without removing desired volume of the part.
2. Presence: Design feature should contribute to at least one surface of the boundaries of the finished part.

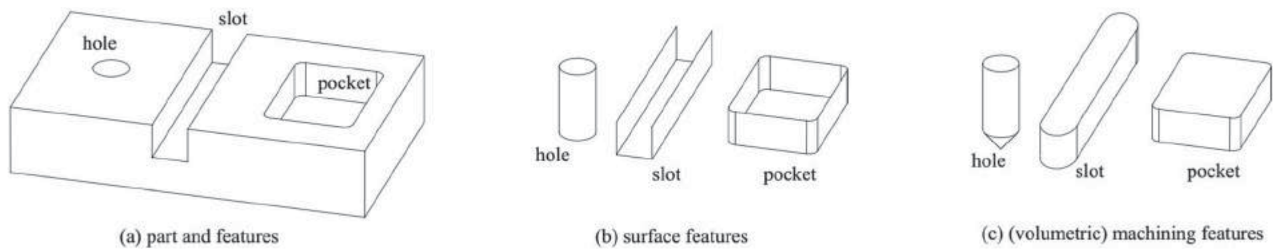

Figure 2. Feature examples for machining operations [4].

3. Accessibility: A negative feature should be accessible to a cutting tool, either directly from open space or indirectly through space created by another feature.
4. Dimensional limits: These limits are imposed by material properties and machining environment. An example of the first is that thin wall features which can't withstand the stress of cutting process. Example for second type is that holes are too deep or too small for drilling tools.

3.2. Manufacturability analysis for AM

Thanks to the 'layer by layer' additive construction mechanism of additive manufacturing, designers are able to design parts with significantly complex geometries by using additive manufacturing process. Although additive manufacturing removes some common constraints for traditional manufacturing, such as tool approach directions and accessibility, there are still many manufacturing restrictions that need to be taken into consideration when designing parts for additive manufacturing. Instead, they are replaced by a different set, including but not limited to those related to CAD, the characteristics of additive manufacturing processes, the capabilities of additive manufacturing devices; material properties, surface finish, enclosed voids, life, costs and environmental requirements. In this paper, the most common restrictions related to characteristics of additive manufacturing processes are researched, in other words, the restrictions caused by fused material, gravity and heat dissipation.

Similar to traditional manufacturability analysis, it is reasonable to identify or describe these manufacturing restrictions and establish the design approaches considering these restrictions in the very early stages of the design phase to avoid the waste of resources. This paper will focus on the geometrical constraints, which are mainly due to unique characteristics of additive manufacturing processes, and identified as follows:

1. Unsupported feature: For example, fused filament fabrication cannot extrude material above open air, so it requires external support structures for overhang, bridge and horizontal hole. Figure 3 shows these three types of unsupported feature, and the red arrows mark the decisive dimensions involved.
2. Minimum feature size: In the additive manufacturing process, thin wall or small size structures are subject to significant thermal dissipation, which may cause various defects, such as un-melted powder inclusions, internal voids, cracks and shape irregularities. Therefore, it is necessary to specify a minimum dimension for thin wall and holes. Figure 4(a) & (b) sketch simple examples for this problem.
3. Maximum vertical aspect ratio: Fused filament fabrication feature cannot have a vertical aspect ratio exceeding a maximum value. Continual the

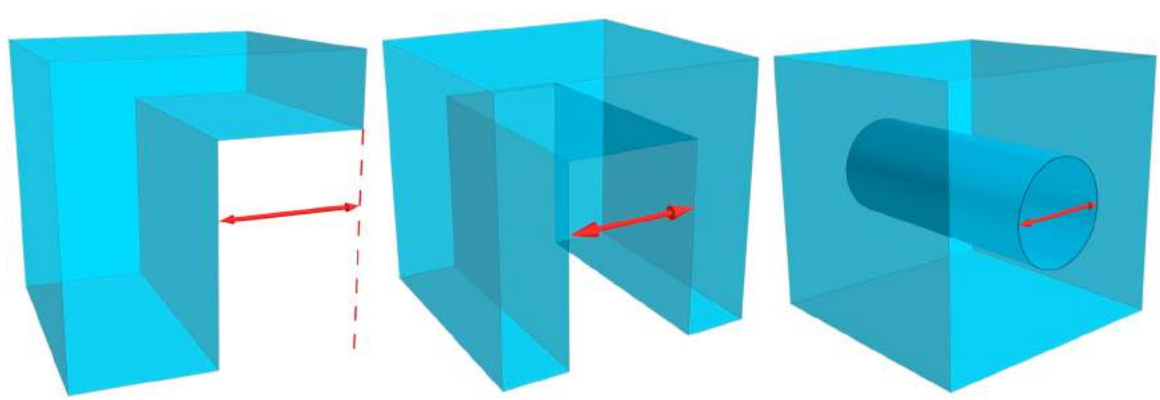

Figure 3. Three types of unsupported feature: overhang, bridge and horizontal hole.

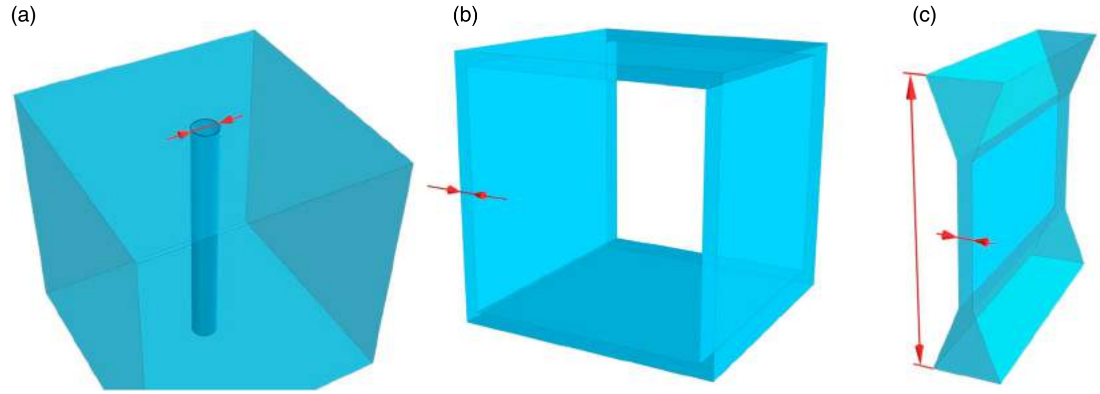

Figure 4. (a) Hole diameter, (b) Wall thickness, (c) Aspect ratio.

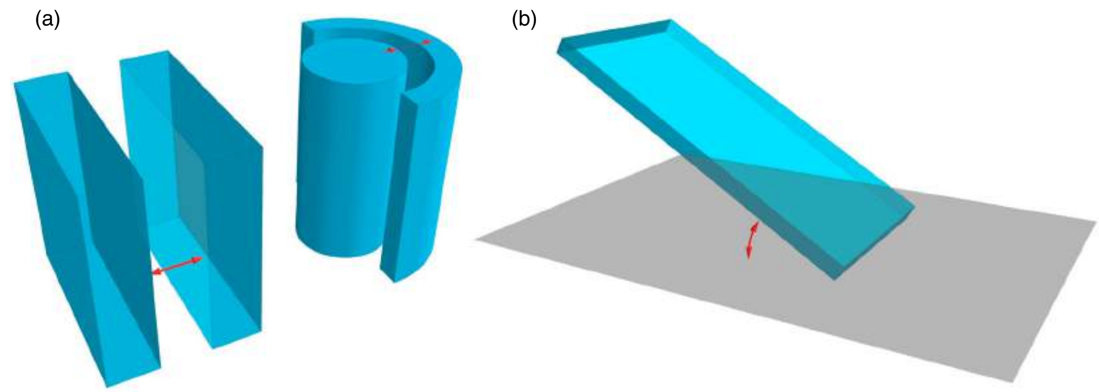

Figure 5. (a) Spacing features between two different surfaces, (b) Self-supporting feature.

recoating process will eventually result in the feature's bending. As shown in Figure 4(c), the aspect ratio is defined as the proportional relationship between feature's height and width.

4. Minimum spacing: For example, in powder melting processes, if two surfaces are too close to each other, heat from one side may influence the properties of the other side. Therefore, it is necessary to specify a minimum spacing between two different surfaces. Figure 5(a) gives two examples for the spacing between two different surfaces.
5. Minimum self-supporting angle: For fused filament fabrication features, it is necessary to set a minimum inclination angle to ensure that angled faces will not collapse without support material. Figure 5(b) shows a schematic demonstration of the angle.

Taking the manufacturability constraints into consideration during design is an important part of the practice – Design for Additive Manufacturing. This topic is well defined and discussed extensively in literatures [16]. All theories concerning Design for Additive Manufacturing can be generally classified in two categories. One is AM-enabled design optimization method and the other is design for additive manufacturing methodologies. Both of these two categories have a conceptual CAD model input as the first step, and the second step is manufacturability analysis, which includes non-geometric analysis and geometric analysis. After that the designer can optimize or redesign the model for other requirements or details.

These design for additive manufacturing systems are focusing on the design process, rules, guidelines, and methodologies. Most of them require human interference and knowledge to interpret and identify the design features. However, few researchers focused on tools for identifying design problems that require examination or providing model correction suggestions. In this paper, an approach using feature recognition is introduced that can aid designers to improve their designs, save resources and expedite the design process.

4. Approach

4.1. Potential feature recognition based on Heat Kernel Signature

Heat Kernel Signature (HKS) is a concise and efficient pointwise shape descriptor developed in computer vison field in recent years. It inherits important properties from the heat kernel, which can fully describe the shape of a surface. Heat kernel signature is directly related to the Gaussian curvature on a surface, and is also closely related to diffusion maps and diffusion distances [14], which means it can describe not only the shape but also the positon of a point on a given domain. In other words, heat kernel signature is able to present the topologic and geometric characteristic of a feature. In this paper, we will illustrate a novel feature recognition technique based on heat kernel signature and apply it to manufacturability analysis for additive manufacturing.

The following paragraph describes the approach adopted to recognize solid model features. For more detailed algorithm, readers are directed e.g. to [5].The application presented is developed in Python and uses the MayaVi visualization engine. The input data is a triangular mesh with coordinates and vertices listed in a text file, and bears resemblance to an STL file. The mesh can be generated through a variety of software, including any finite element analysis software.

The basic idea of HKS is to estimate the heat losses a source endures through time. The rate, at which a source diffuses heat, is deemed an indicator on the topological and geometric entities of a point on a given domain. In order to obtain the rate, the heat diffusion equation is solved, and the solution is the heat kernel, which represents the quantity of heat received by a point after a unit of heat is applied at a certain reference point at the initial time. We define the incremental value of an interval where the heat value on a node persists above a preset threshold as heat persistence value. It can be computed as the integral of the heat function as the area below the heat curve (shown in Figure 6(c)).

Using the heat persistence value and a percentage similarity, the vertices can be clustered into different sets in order to predict a mass distribution pattern and to prepare the potential shape recognition. As shown in Figure 7, these potential features will be separated through a multiscale clustering method. Specifically, using the connectivity of clusters and points, the tip clusters are identified first. Then tip clusters are merged based on similarity and inclusivity for similar subsets at incremented persistence similarity subsets. By extending identified subsets to the faces which they belong to, we can complete the features as a collection of faces, which are detected according to geometric reasoning of vertices.

4.2. Validation on NIST Standard test part

In order to show the feasibility of the presented method, it is validated on a standard test artifact from National Institute of Standards and Technology (NIST). This artifact is designed to quantitatively evaluate the capability and

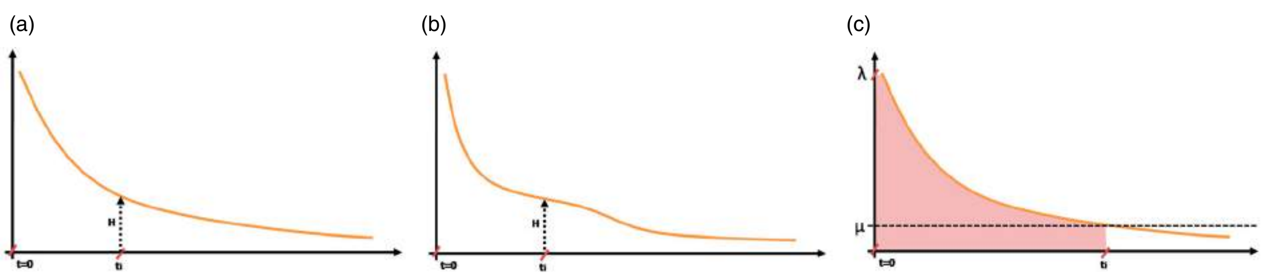

Figure 6. (a) Heat persistence at a typical point, (b) Heat persistence at Point with resistance areas, (c) Heat persistence value shown in red [5].

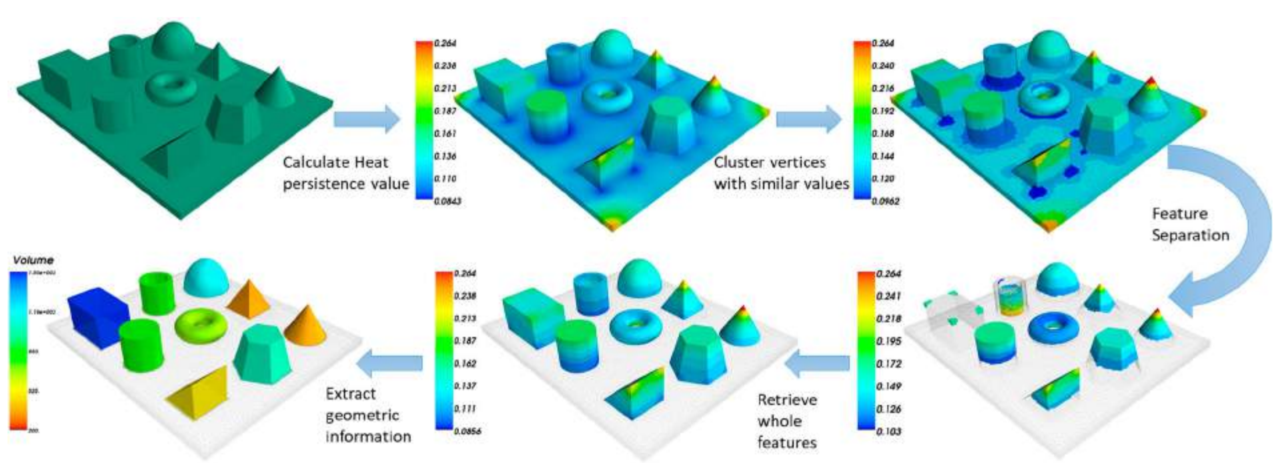

Figure 7. Flowchart of feature recognition process.

to test the limitations of an AM system [9]. As shown in Figure 8, it has multiple features in a variety of size, locations and orientations, which potentially could be features of "real-world" parts. Every feature serves a specific purpose, and the designer intents to test as many manufacturing scenarios as possible. Therefore, these features are also perfectly suitable for testing the developed algorithm.

The input mesh that was used is shown in Figure 9(a), and in Figure 9(b), the result of feature recognition is shown, indicating that 64 features in total are successfully recognized as marked in different colors. Even the feature as small as 0.25 mm in size was well recognized.

In Figure 10, the color of features is marked by the heat persistent value of the vertex that was used for clustering. As introduced in the previous section, features are recognized based on shapes, therefore, the independence and completeness of a feature wouldn't be affected by size and location. Results of two shuffled versions of the NIST part are shown in Figure 11, in which is shown that the features are correctly recognized in these cases as well.

5. Case study

In previous sections, the workings of the proposed methodology to recognize features in the part was discussed. Based on the successful recognition of features, detailed information for the features can be extracted and some desired comparisons or visual displays can be displayed. In section 3.2 five types of manufacturability constraints were defined that need to be inspected before manufacturing. In order to validate feature recognition on these constraints, different sample parts were designed for visually demonstrating the results of the program. For all of these cases, the build direction is assumed along the z direction.

1. Unsupported feature: As shown in Figure 12, after feature recognition to the three different types of unsupported features, each one is sliced layer by layer in the longitude and latitude direction, which can be found by the singular value decomposition of the vertex distribution in the feature. Thereafter,

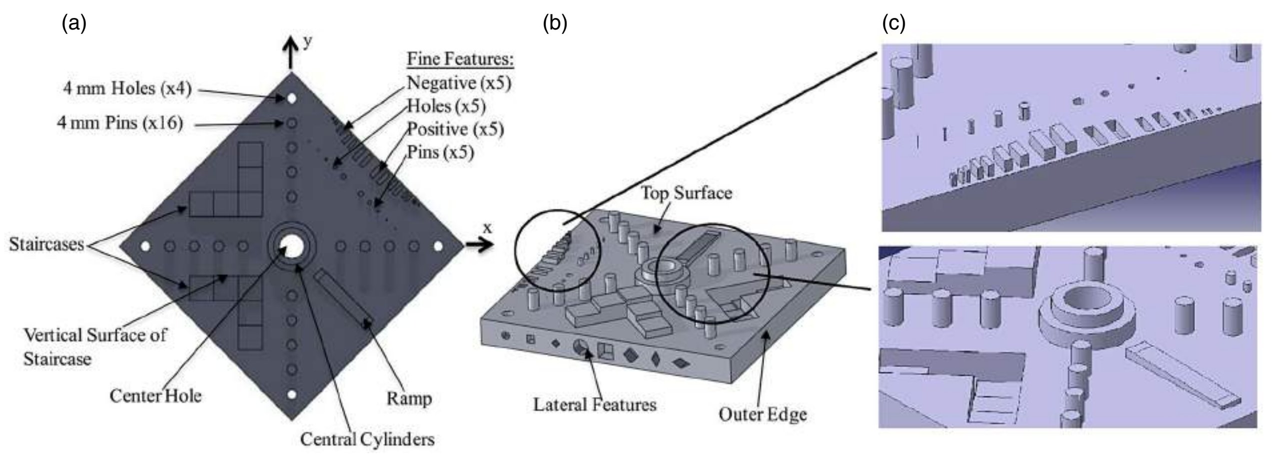

Figure 8. Solid model of the NIST test artifact showing a top view (a) and an oblique view (b) with annotations of important features [9]. (c) Zoomed details of solid model.

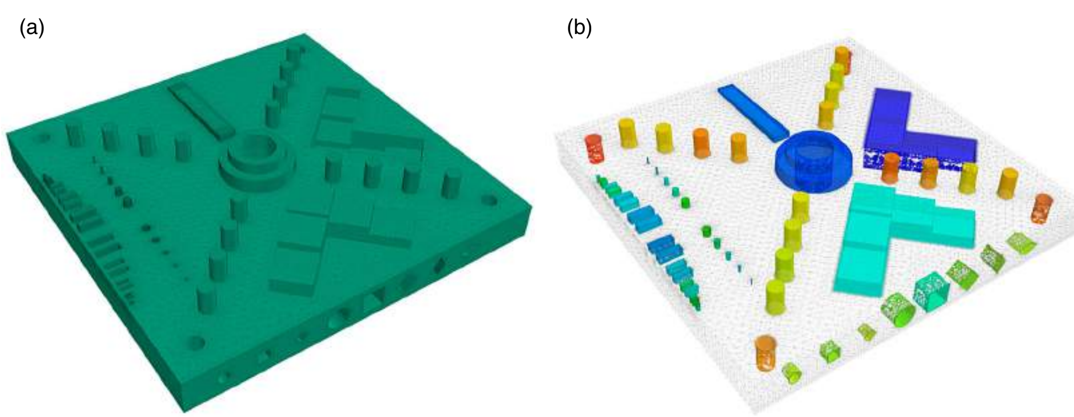

Figure 9. (a) Input mesh of NIST standard test artifact, (b) 64 recognized features shown in different color.

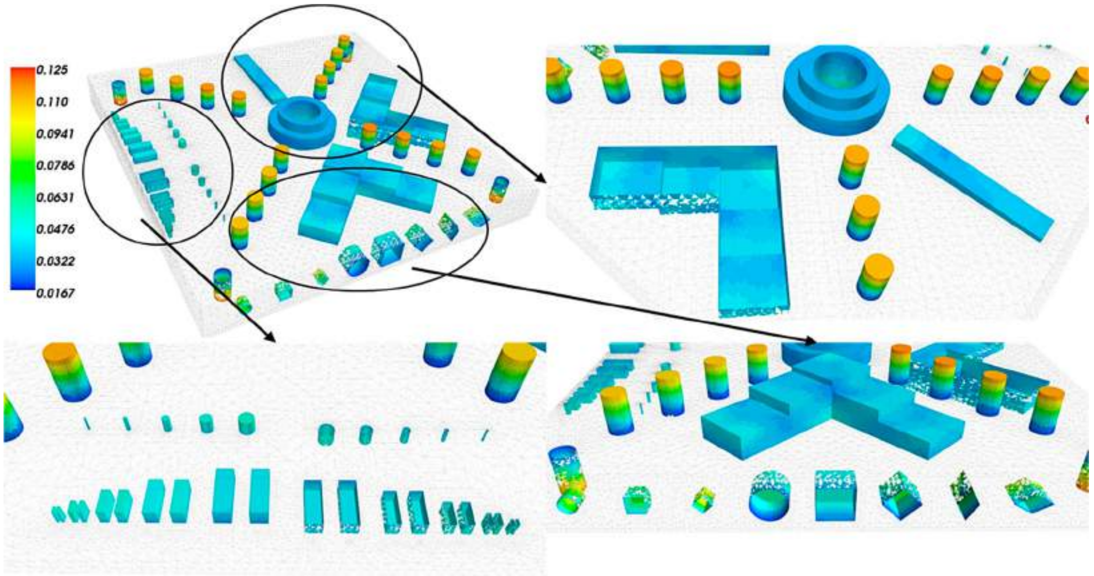

Figure 10. Heat persistent value and enlarged details for the NIST standard test artifact.

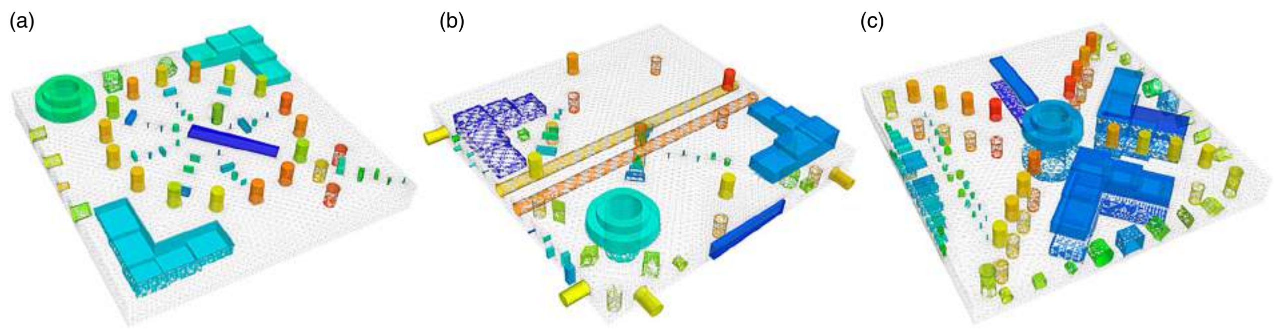

Figure 11. (a) & (b) All the features' locations are changed randomly, (c) all features are mirrored to the other side.

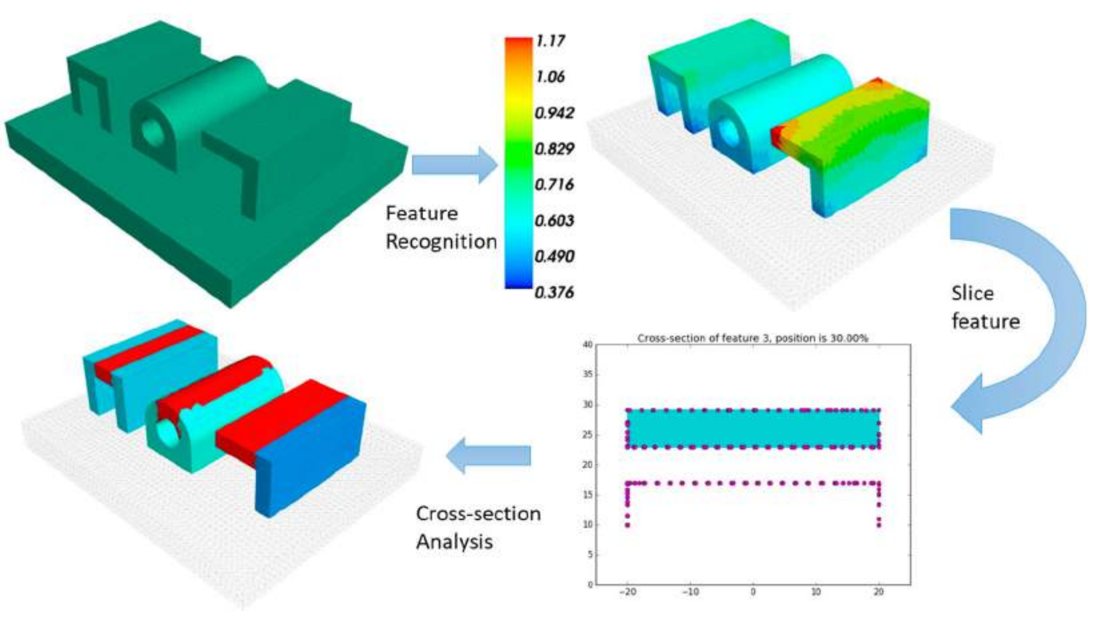

Figure 12. Three types of unsupported features.

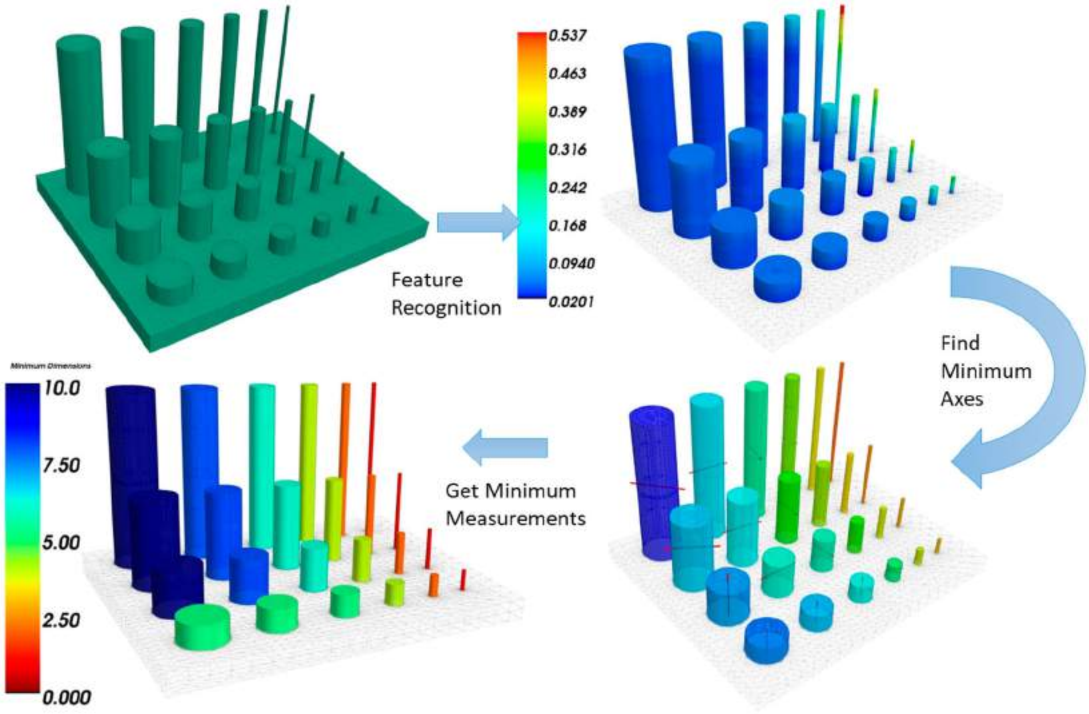

Figure 13. Cylindrical features with different heights and diameters.

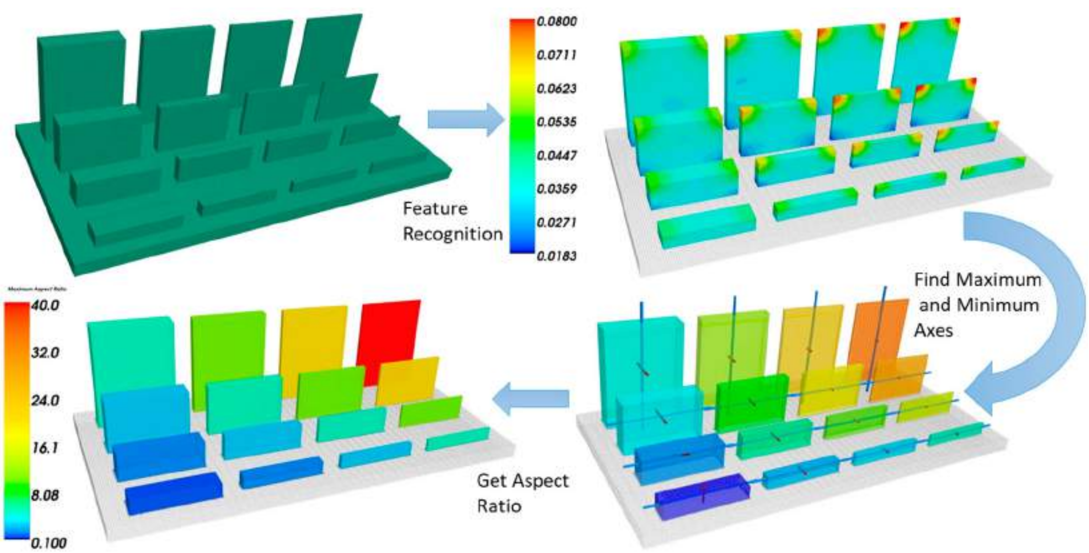

Figure 14. Cubic features with different lengths, heights, and thicknesses.

by analyzing the shape and position of these cross-sections, the corresponding vertices are marked in red color in the last figure.

2. Minimum feature size: In Figure 13, multiple cylindrical protrusions in different length and diameters are built. After feature recognition, three orthogonal axes can be found for each feature by using singular value decomposition. Then the minimum dimension is calculated by projecting vertices to the third axis.
3. Maximum vertical aspect ratio: In Figure 14, cubic protrusions in different length, height, thickness are used for simple demonstration. After feature recognition, the minimum direction and measurement in XY plane can be found by singular value decomposition for each feature. Then the vertical aspect ratio is determined by comparing the height to the minimum measurement. In the last figure, the features are shown in different color indicating the maximum aspect ratio.

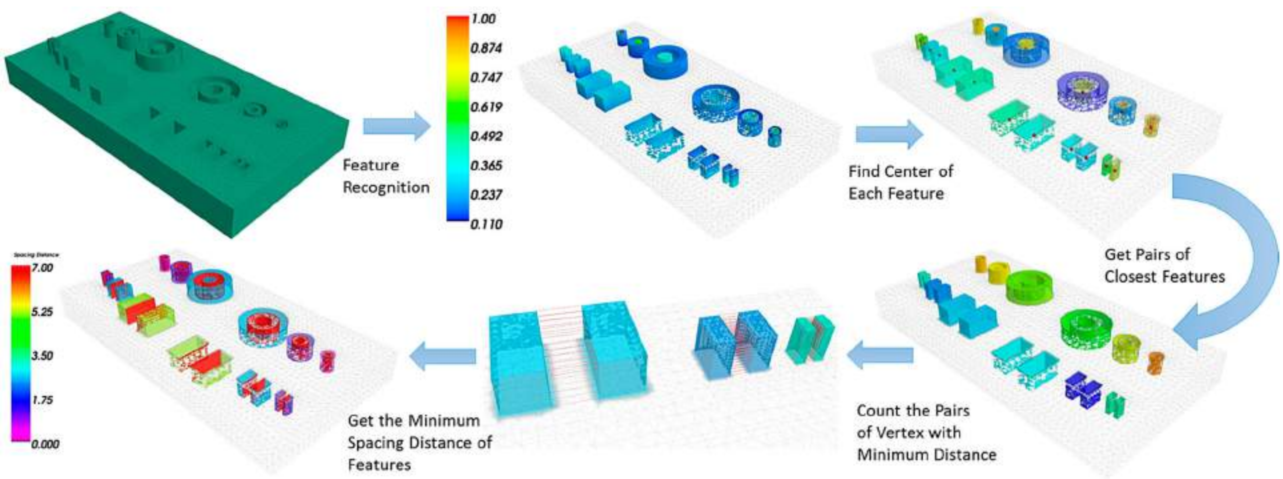

Figure 15. Pairs of protrusions and pockets with different size and spacing distances.

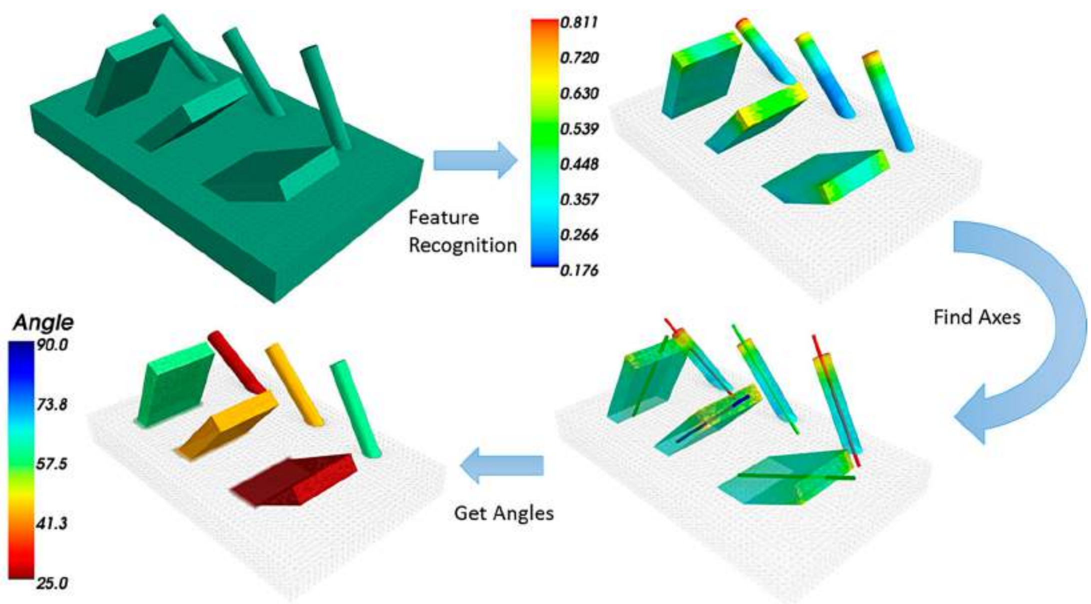

Figure 16. Self-supporting features with different inclination angles.

4. Minimum spacing: In Figure 15, multiple protrusions and pockets are created in different size and spacing distances. First, the center of each feature is found, so features can be divided into pairs that are closest to each other. Then by looping over all the vertices in features, the pairs of vertices with the minimum spacing between the two features are obtained. Finally, the faces which these vertices belong to are marked in red, and the features are shown in colors indicating the spacing distance in the last figure.
5. Minimum self-supporting angle: In Figure 16, three self-supporting features with different inclination angles are built. First, the longitude axes of each feature are found out by singular value decomposition. Then, by measuring the angle between axes and XY plane, the inclination angle of the feature is obtained. In the last figure, features are marked in colors indicating the different angles.

6. Conclusions

In this paper, a new feature recognition method using Heat Kernel Signature is validated for manufacturability analysis of additive manufacturing. The algorithms are described and a NIST standard test artifact is used as an example to demonstrate the feasibility of the method. Further, five key geometric constraints of AM processing are identified and reviewed. Several example part models are designed to demonstrate the feasibility of applying the proposed method for key constraints identification. Future research goals are to incorporate more sophisticated examples to have more rigorous test, to continue to enhance our implementation to other restrictions of AM processing, and to extend our results and application to include more processing techniques and exploring for other possibilities.

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