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turning axis detection,
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AUTOMATIC DETECTION OF AXES FOR TURNING PARTS

This paper delves into a critical aspect of Computer-Aided Production Planning (CAPP): the automated detection of the main rotational axis in turning parts within Computer-Aided Designs (CAD). The identification of the principal turning axis in CAD models presents numerous opportunities in the field of CAPP. In this study, the authors employ advanced surface segmentation techniques to analyse the surface geometry, pinpointing rotational surfaces within the CAD model. Subsequently, significant features are extracted from these identified rotational surfaces, and the necessary data for rotational centers are gathered. By fine-tuning the weighting of the data gathered, the approach can be tailored to suit various planning strategies. This approach has the potential to significantly enhance both the efficiency and accuracy of the automated production planning process for turning parts in CAPP.

1. INTRODUCTION

The design and manufacturing phase plays a crucial role in the product development process. Process planning serves as the essential bridge between design and manufacturing, involving the strategic selection of required manufacturing processes and the systematic determination of their sequences. This aims to efficiently and competitively translate a designer's conceptualized ideas, specifically the designed part, into a tangible component [1]. The conventional method of process planning, relies on the process planner examining the part drawing and manufacturing specifications. This involves identifying comparable parts or features and recalling previous processes. A substantial amount of preparatory work must be conducted before conclusive decisions regarding a manufacturing plan can be reached [2]. In the design stage, diverse CAD technologies have played a significant role in shaping the design process. Concurrently, within the production domain, numerous Computer–Aided Manufacturing (CAM) technologies have had a marked impact on the process of material removal. Regarding the integration of design and manufacturing, CAPP technologies have played a crucial role. CAPP is a modernized approach to managing manufacturing processes,

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replacing the reliance on individual expertise with software-driven solutions. Instead of depending solely on human domain experts to devise production instructions based on design criteria and facility capabilities, CAPP utilizes algorithms and software tools to generate standardized plans, minimizing variability and streamlining the manufacturing process [1]. CAPP proves highly promising in bridging information between CAD and CAM systems, functioning as an automated decision support system for planning the manufacturing process of the product [3]. Planning the machining process for a part is a complex undertaking involving various subtasks such as feature recognition, machine selection, tool selection, setup planning, and operation sequencing [4].

Currently, despite the advancements in manufacturing technology and automation, the integration of CAD and CAM systems does not meet the desired level of closeness. The process planning stage, primarily focused on interpreting design drawings, is often regarded as a bottleneck in the information flow between CAD and CAM. One proposed solution to this issue is the implementation of automated feature recognition [5]. Feature recognition constitutes a pivotal sub-discipline within CAD/CAM, centring on the development and deployment of algorithms designed to identify manufacturing significance within CAD models. It is aptly deemed an essential and foundational element integral to the automation and seamless integration of both design and downstream applications [6]. The initial phase in the feature recognition process for turning parts involves the identification of the main turning axis. Once this axis is ascertained, the turnable component can be deconstructed onto a two-dimensional plane, thereby streamlining the subsequent feature recognition stage.

In the context of axisymmetric components, a discernible turning axis, around which the manufacturing process typically revolves, is readily identifiable to the human observer with a single glance. Object recognition, an impressive cognitive ability of the human brain, is notable for its capability to discern patterns of light received by the eye, accounting for variations in viewing angle, ambient lighting, and distance associated with a given object [7]. Regrettably, the execution of a seemingly straightforward task, such as identifying the turning axis for axisymmetric components, proves to be a computationally intricate challenge. Much like the complexities inherent in the field of feature recognition, the discernment of the turning axis requires the application of sophisticated algorithms.

This paper is motivated by the need for efficient CAPP, where pinpointing turning axes is a crucial first step. This identification is key to streamlining the workload in the planning of turn/mill parts. A tool that adeptly analyses the main axis serves as a cornerstone, facilitating the acquisition of other necessary CAPP elements. The overarching goal is to achieve automated manufacturing planning by systematically leveraging the insights gained from a thorough analysis of the main axis.

2. RELATED WORK

Advanced manufacturing technologies require automation technology that is flexible, fast, and reliable, as it is an indispensable characteristic for their successful implementation [8]. At the present level of technology, CAPP systems are poised to bridge a significant gap in manufacturing tasks, representing another stride toward achieving complete automation in production systems. CAPP systems streamline the process planning task by automating it, reducing the manual effort involved. Considerable preparatory work is necessary before reaching final decisions regarding a manufacturing plan [2]. Employing CAPP can significantly decrease the workload in translating CAD models into process plans. Extensive research has focused on the integration of CAD model data into process planning systems [9].

Significant benefits can result from the implementation of CAPP. In 2020, the manufacturing sector in Europe employed nearly 35 million individuals, constituting 15% of the continent's Gross Domestic Product (GDP) [10]. In a detailed survey of twenty-two large and small companies using generative-type CAPP systems, the following estimated cost savings were achieved:

1. 58% reduction in process planning effort,
2. 10% saving in direct labor,
3. 4% saving in material,
4. 10% saving in scrap,
5. 12% saving in tooling,
6. 6% reduction in work-in-process [11].

Considering the scale of the manufacturing industry, it's evident that implementing CAPP technologies can significantly reduce costs and enhance efficiency. In the context of turning processes, the initial step is automatically detecting axes to initiate the use of CAPP.

Axis detection within CAPP operations is essential for determining the orientation of CAD files, facilitating their alignment along specific axes, and achieving the Maximum Turnable State (MTS). The necessity for axis detection arises from the diversity of CAD software and drawing conventions, wherein different software packages may interpret the XY plane as the top-down plane, leading to inconsistencies even within the same organization or drafting team. Furthermore, there isn't a universally agreed-upon definition for a main rotational axis, and it's possible for there to be multiple solutions to a given problem. For instance, a sphere possesses an infinite number of axes.

In CAPP contexts, addressing these orientation discrepancies traditionally involves manual intervention or the imposition of constraints by programmers mandating a specific X-axis orientation for the part. However, such manual interventions or constraints are impractical in fully automated systems, necessitating software solutions to adapt to varying part orientations.

Axis detection not only resolves orientation issues but also facilitates the calculation of the MTS for parts. The MTS signifies an intermediate state during manufacturing where further material removal by turning would result in surface imperfections on the final part. Conceptually, the MTS corresponds to a solid of revolution. Recognizing the MTS is pivotal in devising efficient process plans for Mill/Turn operations, where turning processes offer superior efficiency compared to milling. Consequently, identifying the MTS is fundamental for optimizing production strategies, as highlighted by Yip-Hoi and Dutta, 1997 [12].

2.1. CAPP

CAPP serves as the linchpin connecting various stages in the design and manufacturing processes by optimizing conditions. Within Computer Integrated Manufacturing (CIM) systems, the role of developed CAPP systems is pivotal for advancing manufacturing engineering. Fig. 1 provides a concise overview of the position of CAPP within the manufacturing process.

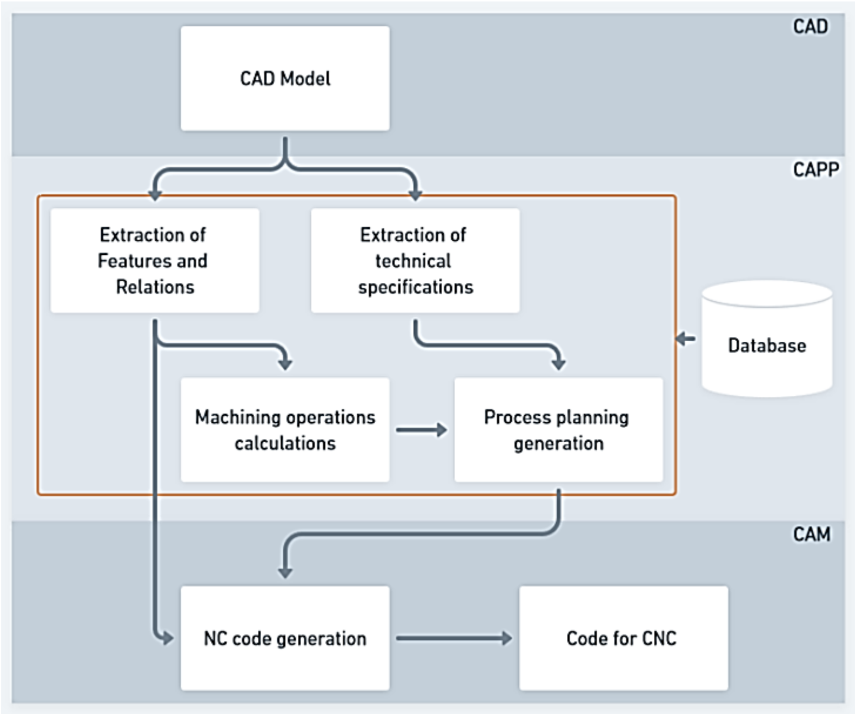


Fig. 1. CAPP processes and their role in manufacturing

However, the term CAPP has not been used uniformly since around 1965. CAPP is described as use of computer technology to assist in the planning of manufacturing processes. This includes activities such as determining the sequence of operations, selecting appropriate tools and equipment, estimating process times and costs, and generating instructions for manufacturing operations. CAPP systems typically integrate with CAD systems to utilize product design information in the planning process, aiming to improve efficiency, accuracy, and consistency in manufacturing planning and execution.

Different authors have described CAPP in different ways. For instance, Yusof and Latif [13] characterize CAPP as utilizing computer technology to support process planners in their planning tasks, recognized as a crucial component of CIM. This encompasses identifying the processes and parameters essential for converting a block into a final part or product.

While Yusof and Latif gave a narrow description for CAPP, Isnaini and Shirase gave a wider description for CAPP. Isnaini and Shirase [3] has included several steps into the category of CAPP. These steps are selection of manufacturing resources, selection of cutting condition, selection of tool path, selection of setup and, selection of manufacturing operation and their sequences.

What unites both descriptions are their shared acknowledgment of the utilization of computer technology to assist planners in their planning tasks. This entails leveraging software and digital tools to streamline processes, optimize resource allocation, and enhance overall efficiency in manufacturing planning. Additionally, they both underscore the significance of CAPP within the broader framework of computer integrated manufacturing. This recognition highlights the pivotal role that CAPP plays in integrating various manufacturing processes and technologies to achieve seamless production workflows and improve overall productivity.

The primary functions of CAPP operations revolve around selecting the appropriate machine tool, machining operations, cutting tool, and determining the cost and time required for part production. These operations start by considering both the available facilities and the desired quality standards for the manufactured parts. Subsequently, the CAPP algorithm is applied to the manufacturing process, aiming to achieve optimized conditions for part production that align with the specified quality standards and operational constraints [14].

The conceptualization of process planning through computerized means traces its origins back to 1965, as articulated by Neibel [15]. Subsequent to this seminal work, the domain of CAPP has witnessed a profusion of research endeavors [1].

Kyprianou is credited with pioneering the concept of feature recognition, which involves identifying topological and geometric patterns within CAD databases and then comparing them to characterize specific shapes, known as features, that require identification [16, 17]. Following Kyprianou's work, other ideas are incorporated into the research. Face adjacency graphs are developed for boundary representation of solid objects by Ansaldi in 1985 [18]. In 1984, Henderson developed a rule-based feature detection which uses a database containing edge, face and vertex information of predefined features [19]. In 1982, Woo conducted early research in feature recognition by identifying cavities in objects using Constructive Solid Geometry (CSG) representations. This method relied on spatial relationships among primitive volume faces. In a subsequent study in 1983, he devised an algorithm to detect features by decomposing objects into a series of volumes. However, the algorithm's effectiveness varied for different shapes, and the resulting volumes were not always primitive solids [20, 21].

In 1990, Sahay et al. [22], pioneered feature recognition in cylindrical shapes by introducing a method comprising a systematic six-step process for decomposing a 2D representation of a cylindrical turning part:

1. Initial pre–processing of geometric data to prepare for analysis.
2. Categorization and precise marking of edges to delineate key structural elements.
3. Extraction of feature subgraphs to identify distinct geometric patterns.
4. Classification of features into simple and complex categories based on their structural complexity.
5. Structuring a hierarchical organization of complex features to establish relationships and dependencies.
6. Precise identification of features through a rigorous analytical process.

This methodological framework not only laid the foundation for feature recognition in cylindrical shapes but also underscored the importance of systematic and structured approaches in geometric analysis and feature identification in manufacturing processes.

Sahay et. al. proposed a method that operates on 2D representations of turning parts. These representations are obtained manually and utilized within the algorithm to detect features. Obtaining the cross-section of a turning part manually essentially entails performing all the work to calculate the maximum achievable state for turning operations.

In the context of CAPP and CIM, the ultimate objective is the full automation of every stage to achieve a manufacturing planning system devoid of human intervention. The detection of the main rotational axes of turnable parts assume a critical role in automating the process of feature detection within such parts.

2.2. AXIS DETECTION

The difficulty of detecting a main rotational axis arises from the fact that functional components do not consistently exhibit axisymmetry, although they may possess some level of axisymmetry that renders them suitable for turning operations either before or after undergoing other, more costly machining processes. Consequently, there is a need for a precise method to approximate the axisymmetry of a part with arbitrary geometry around a specified axis [23].

This problem is scarcely addressed in literature due to its perception as a designer-centric issue, presumed to be resolved through human intervention. A few methodologies resort to volume decomposition to ascertain the rotation axis, which proves ineffective for non-axisymmetric features such as milling features. Zubair and Mansor [24] found it necessary to incorporate a defeaturing process into their algorithm to proceed with volume decomposition effectively. Their defeaturing operation involves selecting a planar face from the front plane of a half-section part model body for the revolve process. The resulting revolved body is subsequently subtracted from the original part model using Boolean operations to eliminate features that lack axis-symmetry.

In 1997, Rico et. al. [25] employed a 2D approach to obtain CAPP procedures, leading up to automatic NC programming. By using a 2D approach, the authors eliminated the need for defeaturing and the part center automatically became the turning axis. However, this approach needs 2D interpretations of complex mill/turn parts to be prepared in addition to 3D CAD files.

One of the solutions to main axis detection in literature is the algorithm developed by Zubair and Abu Mansor [26] which focuses on precise axis detection for orienting cylindrical part models. Initially, the algorithm identifies planar faces by analysing the normal vectors of the x, y, and z-axes within the 3D CAD model. This step enables automatic rotation of the CAD model to ensure correct positioning for subsequent calculations and machining setups. The meticulous detection of normal vectors of planar faces allows the algorithm to determine the vertical alignment of the part and make necessary adjustments for proper orientation. Additionally, the algorithm progresses to identify circular faces, enhancing face generation for further processing. This meticulous approach to axis detection highlights the algorithm's dedication to achieving accurate part orientation, a crucial aspect for successful machining operations.

Another approach is proposed by Behandish et al. [23] for automating the process of determining the main rotational axis based on solving an eigenvalue/eigenvector problem. They introduced a turnability ratio, can be seen Fig. 2, calculated by revolving the part on candidate axes and conducting a 3D sweep. The goal is to maximize this ratio, indicating higher efficiency in the turning process.

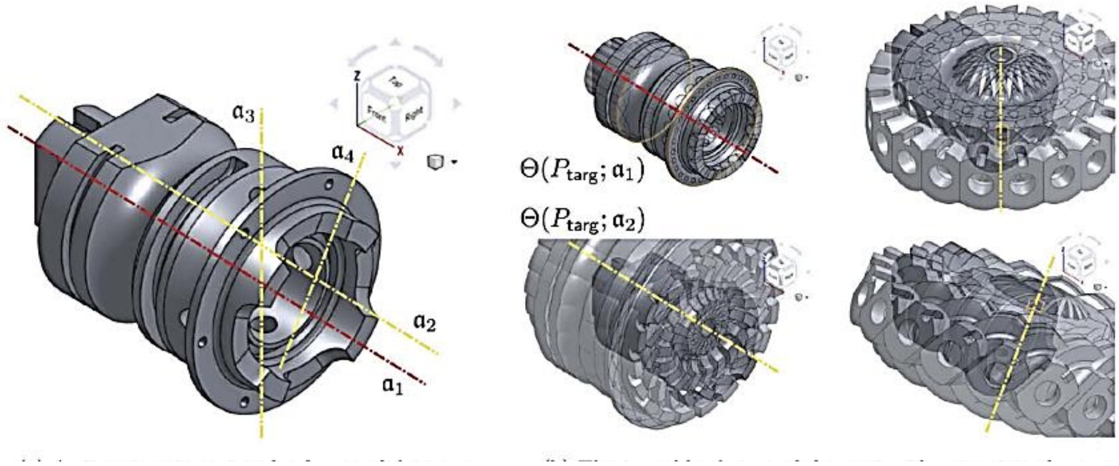


Fig. 2. Turnability ratio [23]

For axisymmetric parts, the turning axis is obtained through eigen–analysis. However, for non-axisymmetric parts, a method to identify the optimal axis is needed. The authors proposed a methodology based on evaluating the turnable closure (TC) of the part around a candidate axis. This involves computing the volume difference between the original part and its TC, aiming to minimize this difference for efficient machining.

The methodology was illustrated through explicit and implicit approaches, demonstrating the computation of turnable closures and turnability ratios. The authors emphasized the importance of considering fixturing constraints, tool geometry, and setup for a more comprehensive analysis [23].

The detection of rotational surface axes can also be done using several methods like Hough Transfoms, Random Sample Consensus (RANSAC) [27] or Convex Hull algorithms [28]. The Hough Transform presents a significant challenge due to its computational demands in both time and space. With industrial parts CAD files containing millions of points, the Hough Transform becomes impractical for objects with more than three parameters [27]. Like Hough Transform, RANSAC can also be used to detect an axis. However, this approach assumes a limited number of cylinders within the scene and may fail in scenarios featuring multiple cylinders with varying radii along a single orientation [27]. While such limitations are present in both methods, using a Convex Hull algorithm may yield to better results in detection of rotational axes. Kreveld and Löffler showed that using the Convex Hull algorithms there are polygons called k-gon's which have a random finite number of sides that can represent a circle [28].

Within existing literature, numerous methodologies have been explored for determining turning features applicable in CAPP, each with inherent limitations. Certain methods involve the use of components lacking non-axisymmetric characteristics, thereby positioning the primary rotational axis at the center of the CAD drawing. Zubair and Mansor [24] provide an illustration of this approach. Certain methodologies specifically employ the 2D depiction of revolute solids, as demonstrated by Kim and Cho [29] and Rico et al. [25]. While these limitations and prerequisites are suitable for theoretical investigations, achieving full automation of a turning process necessitates a robust methodology capable of handling parts in any orientation. To achieve this goal, successful detection of a main rotational axis is paramount.

3. METHODOLOGY

This paper's proposed method can be applied to parts which have more than one cylindrical or conical feature, which have centres lying along the main turning axis. The method can be divided into two parts:

1. Selection of candidate axes
2. Selection of the most suitable axis

The initial phase involves the identification of rotational surfaces, marking the foundational step towards determining the main rotational axis. Subsequently, the centers of the identified features are computed. Following this computation, the calculated centers undergo a weighting process, wherein their respective weights are assigned based on considerations such as height, radius, and surface area.

3.1. SELECTION OF CANDIDATE AXES

In this study, the characterization of rotational faces includes both cylindrical and conical configurations. This deliberate selection is predicated upon the prevalence of cylindrical and rotational faces as primary components fashioned through turning processes in manufacturing.

3D geometry used in the algorithm is represented using meshes. In meshed solids, slicing perpendicular to the rotation axis reveals a surface geometry which is a regular polygon. To leverage this characteristic, the detection of rotational surfaces is carried out using methodologies from “Approximating Largest Convex Hulls for Imprecise Points” by Kreveld and Löffler [28] and “A Survey on Mesh Segmentation Techniques” by Shamir (2008) [30].

For every identified rotational surface on the component, an axis of revolution is computed and stored as a vector that spans the height of the respective feature. A random point on the calculated axis of a rotational feature is selected for each rotational surface which are going to be used as centre points for detected rotational surfaces in the next steps. Subsequently, the cross-product values between the vectors were computed. Notably, when the vectors are linearly dependent, implying they are either collinear or anti-collinear, cross-product values equate to zero. Leveraging this mathematical property facilitates the identification of points situated along a specific axis within the 3D file.

Two vectors are formed using three points, denoted as A, B, and C. These points are selected from a pre-existing list of centre points obtained in the preceding step, and the iteration process continues until all possible combinations of points are tested for linearity.

This categorization method facilitates the clustering of points, thereby enabling the identification of suitable axes. This systematic approach to point classification serves as a foundation for detecting candidate axes within the dataset. The graphical representation of the algorithm can be seen on Fig. 3.

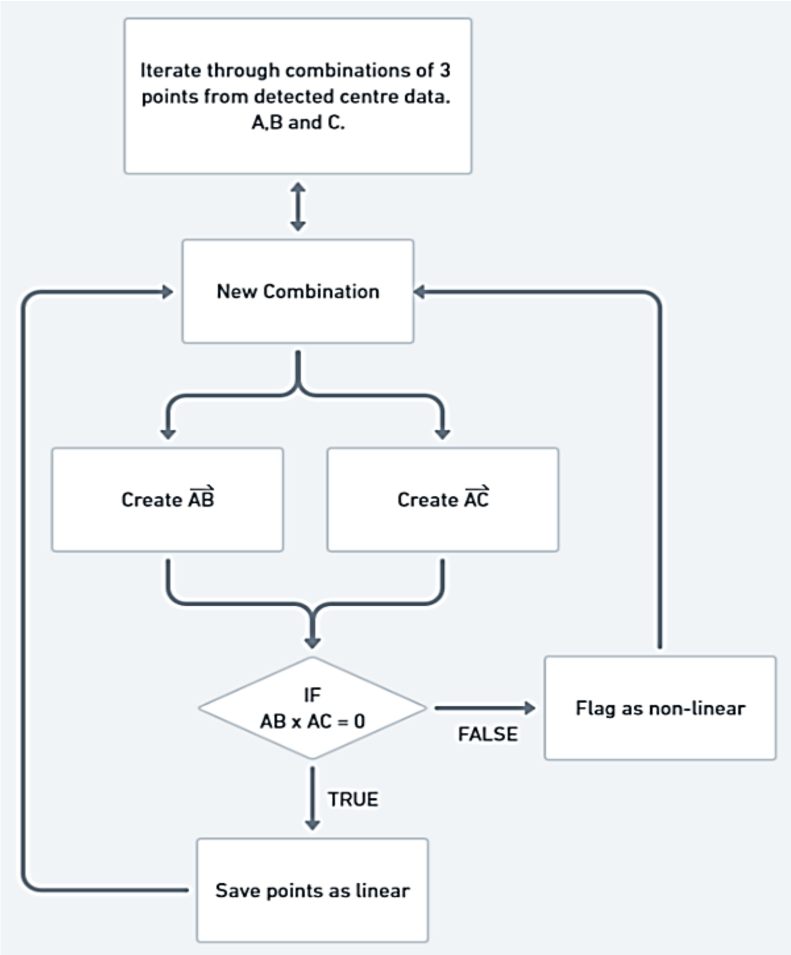


Fig. 3. Graphical representation of the algorithm

3.2. SELECTION OF THE MOST SUITABLE AXIS

Utilization of weighted factors serves as a pivotal strategy, endowing the algorithm with the capability to discern and prioritize the significance of distinct features within the given part. By assigning appropriate weights to these features, the algorithm is empowered to accurately identify a rotational axis which contains the centres of highest weighted centres of rotational features, for turning parts, thereby enhancing the overall effectiveness of the detection process.

Cross product of vectors is collected and the values which are zero are considered along the same axis and linear, within a certain error margin. Although the error margin is typically minimal, the diverse range of file types and representations of CAD files necessitates the existence of an error function.

Exploiting this inherent property facilitates the identification of points coexisting along a shared axis. However, establishing co-planar points alone does not ensure the accurate detection of a main axis, given the substantial diversity in part complexity and the distribution of rotational elements. Creation of two vectors from the rotational centres can be seen in Fig. 4.

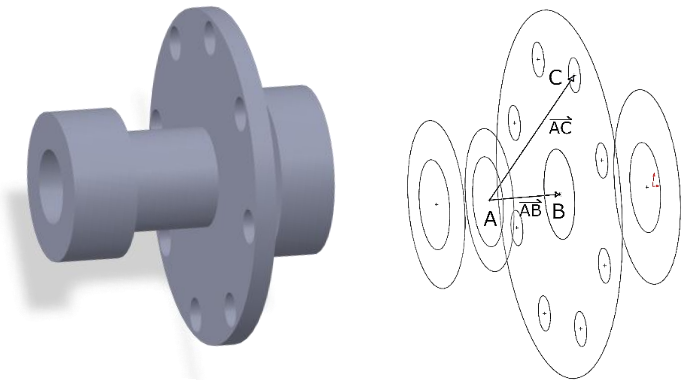


Fig. 4. Vector creation from 3 points

Notably, the presence of numerous small concentric holes, each comprising multiple rotational elements, may yield linearly aligned points, potentially leading to computational inaccuracies as can be seen in Fig. 5.

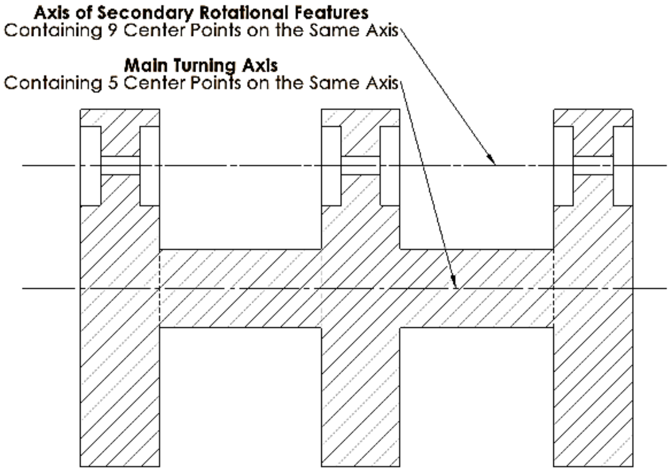


Fig. 5. False detection of main rotational axis

To address the aforementioned challenge, a strategic approach is implemented by incorporating a weighted function within the framework. Weights are assigned to the center points based on the length, area and radius values of their parent features. This weighting approach facilitates the identification of the "heaviest" axis, typically utilized for producing turning parts. The weighing function in the algorithm can be seen in equation 1.

$$\text{Weight} = \text{Face Length} * \text{Face Radius} * \text{Face Area} \tag{1}$$

While certain unconventional design elements may lead to erroneous results, these designs are not typically manufactured through turning processes and thus fall outside the scope of this method.

4. RESULTS AND DISCUSSION

The assessment of the detection algorithm's performance involves the utilization of a set of diverse rotational part files. A total of 12 files have been selected for analysis. The results of the experiment can be seen on Fig. 6. The disparities between the calculated axis and the defined axis are presumed to arise from discretization errors stemming from the discrete representation of surface triangles. The meshing introduces specific inaccuracies due to rounding errors and the discretization of smooth curves, resulting in a characteristic tessellated surface. These errors inevitably lead to some uncertainty regarding the accurate size and position of features when extracting information from meshed solid data [31]. As Qiu et. al. [32] stated, it is always a tradeoff between triangle count and geometric accuracy.

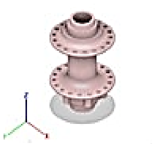
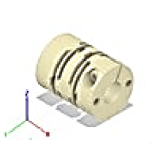
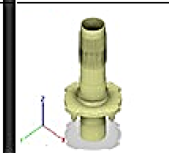
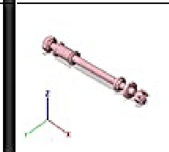
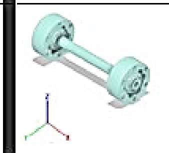
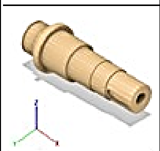
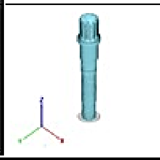
Part	Part Information	Defined Turning Axis (From 0,0,0)	Detected Turning Axis (From 0,0,0)	Error	Part	Part Information	Defined Turning Axis (From 0,0,0)	Detected Turning Axis (From 0,0,0)	Error
	Triangle Count 28330 Bounding Box L: 6832 mm W: 6832 mm H: 10990 mm	x = 0 mm y = 0 mm z = -1 mm	x = -0.001 mm y = 0.001 mm z = -0.999 mm	x = 0.001 mm y = 0 mm z = 0 mm		Triangle Count 19112 Bounding Box L: 216 mm W: 216 mm H: 333 mm	x = 0 mm y = 0 mm z = -1 mm	x = 0 mm y = 0 mm z = -1 mm	x = 0 mm y = 0 mm z = 0 mm
	Triangle Count 3838 Bounding Box L: 260 mm W: 200 mm H: 200 mm	x = 1 mm y = 0 mm z = 0 mm	x = 0.999 mm y = 0 mm z = 0 mm	x = 0.001 mm y = 0 mm z = 0 mm		Triangle Count 5736 Bounding Box L: 1230 mm W: 1230 mm H: 2570 mm	x = 0 mm y = 0 mm z = 1 mm	x = 0 mm y =0 mm z = 0.999 mm	x = 0 mm y = 0 mm z = 0.001 mm
	Triangle Count 6658 Bounding Box L: 615 mm W: 940 mm H: 940 mm	x = 1 mm y = 0 mm z = 0 mm	x = 0.999 mm y = 0.002 mm z = -0.004 mm	x = 0.001 mm y = -0.002 mm z = 0.004 mm		Triangle Count 15771 Bounding Box L: 112.50 mm W: 15 mm H: 15 mm	x = 1 mm y = 0 mm z = 0 mm	x = 0.999 mm y = 0 mm z = 0 mm	x = 0.001 mm y = 0 mm z = 0 mm
	Triangle Count 6966 Bounding Box L: 2555 mm W: 381 mm H: 381 mm	x = 1 mm y = 0 mm z = 0 mm	x = 0.999 mm y = 0.001 mm z = -0.006 mm	x = 0.001 mm y = -0.001 mm z = 0.006 mm		Triangle Count 28330 Bounding Box L: 6832 mm W: 6832 mm H: 10990 mm	x = 1 mm y = 0 mm z = 0 mm	x = 1 mm y = 0 mm z = 0 mm	x = 0 mm y = 0 mm z = 0 mm
	Triangle Count 11453 Bounding Box L: 1600 mm W: 1600 mm H: 4260 mm	x = 0 mm y = 0 mm z = 1 mm	x = 0 mm y = 0.005 mm z = 0.999 mm	x = 0 mm y = -0.005 mm z = 0.001 mm		Triangle Count 11750 Bounding Box L: 435 mm W: 430 mm H: 800 mm	x = 0 mm y = 0 mm z = -1 mm	x = 0 mm y = 0 mm z = -0.999 mm	x = 0 mm y = 0 mm z = -0.001 mm
	Triangle Count 3252 Bounding Box L: 22 00mm W: 750 mm H: 750 mm	x = -1 mm y = 0 mm z = 0 mm	x = -0.999 mm y = -0.001 mm z = -0.001 mm	x = -0.001 mm y = 0.001 mm z = 0.001 mm		Triangle Count 2528 Bounding Box L: 1000 mm W: 1000 mm H: 5080 mm	x = 0 mm y = 0 mm z = 1 mm	x = 0 mm y = 0 mm z = 0.999 mm	x = 0 mm y = 0 mm z = 0.001 mm

Fig. 6. Experimental data of 12 rotational parts

In addition to errors resulting from discretization, uncertainties may arise in the geometric analysis. In some instances, multiple solutions might exist, with one being preferred by the user. In such cases, the "weights" presented in this algorithm can be utilized.

These weights can be adjusted based on user needs for attributes such as surface quality, turning machine type, or material type. This ability to influence the outcome of automated axis detection allows users to tailor the algorithm to their specific requirements, thereby minimizing errors and uncertainties.

The presented methodology offers the means to compute the main rotational axes of components featuring multiple rotational attributes. However, it is important to note that components possessing singular rotational attributes, such as a solid cylindrical bar or a solitary conical part, are not amenable to assessment using this approach.

Moreover, the precision of the results is contingent upon factors including the intricacy, resolution, and variability inherent in the meshed file. The method involves the pairwise matching of points, leading to a cascade of operations with a cubic growth in complexity relative to the point count. Consequently, computational expenses may escalate significantly for components characterized by an elevated number of rotational features and intricate geometries.

In the investigation conducted by Baturynska [33], an intriguing assertion was put forth, positing a noteworthy correlation between the quantity of mesh triangles and the tangible dimensions, namely width, thickness, and length, of a given component. This proposition was substantiated through the application of two-tailed Pearson correlation tests, underscoring the empirical basis of the claim. Moreover, Valentan et al. [34] contributed to this discourse by elucidating that rotational element, such as wheels, exhibit a substantially higher prevalence of triangles compared to planar surfaces.

Given the specific focus of our current study on rotational elements, it becomes imperative to recognize the pivotal role that mesh, B-Rep or CSG quality plays in shaping the outcomes of the main rotational axis analysis. Notwithstanding these limitations, the proposed method holds potential for streamlining processes such as CNC machining, 3D printing, and other manufacturing endeavors involving elements with rotational attributes.

The algorithm serves as a foundational framework for the inception and advancement of algorithms pertinent to the automated production planning of rotational components. The identification of a main axis for turning facilitates the derivation of the maximum turnable state, consequently simplifying the analysis of these components to a 2D section representation as opposed to a voluminous 3D object replete with numerous vertices. This reduction in dimensionality effectively mitigates the computational overhead associated with automation processes.

Primarily, our method excels in the detection of main rotational axes independent of the orientation of CAD files. This obviates the necessity for predefined alignments, allowing for flexibility wherein the part may exhibit the X axis or any arbitrary vector within three-dimensional space as the rotation axis. Furthermore, from a computational standpoint, our method entails solely basic vector multiplications and comparisons, thereby resulting in minimal demands on both memory and processing power.

Moreover, our algorithm adeptly handles intricate geometries and the presence of multiple non-axisymmetric facets, ensuring that the integrity of results remains unaffected by such complexities.

The selection of rotational surfaces includes various facets within the entire component, including holes, pockets, chamfers, and cylindrical structures both inside or outside of the part. The rationale behind this inclusive approach lies in the possibility that their respective centers may coincide with the main rotational axis. Consequently, all these features are considered as potential candidates for incorporation into the proposed algorithm. Despite the likelihood of their axes being situated elsewhere, the algorithm is designed to filter out such features, ultimately opting for those exhibiting uniaxial alignment and possessing the most pronounced significance.

In addition, rotational surfaces characterized by multiple centers, such as ellipses, are deliberately excluded from consideration within the algorithm. This exclusionary measure is implemented due to the potential to introduce inaccuracies in the calculations, as the presence of multiple centers complicates the unambiguous determination of a main rotational axis.

Turn-milling generates surfaces that are non-cylindrical, effectively producing polygonal shapes as the end result [35], rotational surfaces are rarely complete and usually they are cut in different ways to create extra features such as cut cones, key ways or boring holes. One part with incomplete surfaces can be seen on figure 7.

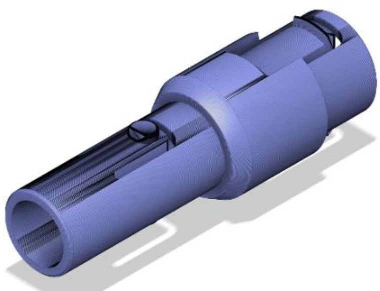


Fig. 7. A rotational part with incomplete revolving surfaces

The proposed method also considers those cut and incomplete rotational faces in calculations.

Future endeavors will focus on integrating the proposed detection method into the domain of feature recognition. This integration aims to enhance feature recognition capabilities specifically tailored for turning parts, while also effectively discerning between milling features. By accomplishing this, the objective is to develop a comprehensive system that enables fully automated production planning for mill/turn parts.

In summary, the future trajectory of this research entails a multidisciplinary approach encompassing advanced algorithm development, machine learning techniques, integration with existing software ecosystems, and continuous refinement of detection methodologies. By pushing the boundaries of feature recognition in turning parts and mill/turn applications, the ultimate goal is to empower manufacturers with a robust, fully automated production planning solution capable of optimizing efficiency and productivity in machining operations.

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