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ORIGINAL ARTICLE

Critical assessment of Shape Retrieval Tools (SRTs)

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Abstract

In today's design — manufacturing context, designers often modify existing 3D shapes (or design models) instead of creating a new design from scratch. This requires the ability to search an existing database of designs/3D models to identify and extract similar designs. Shape Retrieval Tools (SRTs) have been developed to provide an essential role in saving time and effort to retrieve and generate new designs. The capabilities of commercially available SRTs vary based on the form of the input design model, the search technique or algorithm used, the search/retrieval time, ease of use, and the quality of results. The focus of this paper is to study of their capabilities, performances, and differences and develop criteria to compare the effectiveness and performance of such Shape Retrieval Tools. Current search evaluation methods, such as precision and recall, are based on human interpretation of the results. This paper presents a holistic set of metrics for comparing the performance and effectiveness of SRTs, including data input options (to search), effectiveness of the search process, the associated retrieval time, overall ease of use, and additional data retrieval details. An algorithm is proposed to objectively analyze the search results based on the proposed Model Match Ratio (MMR), computed by the variance between the input and retrieved geometries. The search results are usually presented in a rank order list. A Precision Sequence Metric (PSM) is developed to evaluate the retrieved list by ranking the retrieved results based on the MMR for evaluating the quality of the search. The proposed evaluation algorithm was tested on several design models (and their subsequent retrieval results) involving three SRTs (Vizseek, Geolus, and CADENAS); the results of the comparison of the performance of these SRTs are discussed in this paper.

Keywords Shape Retrieval Tools (SRTs) · Model Match Ratio (MMR) · Precision Sequence Metric (PSM)

1 Introduction

In recent years, most new designs are essentially variations/ modification of existing designs. In this context, the computer-based automation of identifying existing designs (or CAD models) based on a given input model's design or shape attributes assumes significance [1, 2]. Such an automated retrieval of similar part designs by Shape Retrieval Tools (SRTs) can reduce the lead time to design new parts in design-manufacturing applications. The role of SRTs assumes significance due to their role in enabling engineers to retrieve existing designs. There are several SRT tools in the market, currently whose capabilities and performance differ widely. The study of their capabilities, performances, and differences is the focus of this paper and identifies criteria to determine the effectiveness and performance of such Shape Retrieval Tools.

Typically, SRTs can search a target database or a repository of files on the web to retrieve similar part designs. As shown in Fig. 1, the search engine's whole database is the entire 3D model collection. After the search process, all the models returned by the search engine are collections of retrieved models. The relevant models represent the geometries that are closely related to the input part. The search algorithms may retrieve models that are not relevant. There may be several relevant models, but only a subset of those may the ones that are relevant retrieved models. One of the problems is how

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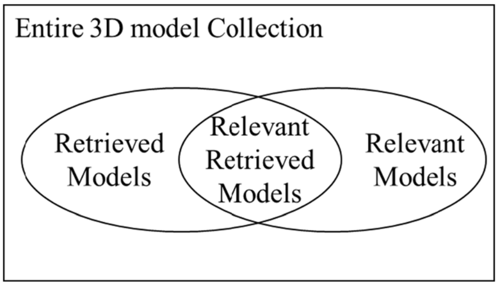


Fig. 1 General selection similar objects [3]

to determine the relevant models without human interaction or justification.

As shown in Fig. 1, when performing a query, the intent is in retrieving models based on a target or input design or model from the set of the relevant models. However, the search may also retrieve models that are not relevant. The emphasis should be on ensuring that the search process restricts itself to the relevant models. Design retrievals can be performed using various techniques, including using properties based on Gaussian curvature, Normal variations, Midpoints [4], and contour frequency [5] match. These search methods share one aspect in common: converting 3D models into various 2D representations and then subsequently storing them in 1D space. Depending on the choice of the retrieval algorithm, the stored 1D data of the associated 3D model are different, thus the outcomes will vary. In addition, the 1D signal is highly correlated with the corresponding 3D model geometric center, orientation, and volumetric information. The results of a search which highly relies on the 1D signal can be easily altered when the corresponding 3D model geometric center, orientation, and volume changes while the topological information of the 3D model still remains the same. Ideally, an effective SRT should extract the most relevant models based on the target or input design model and present them after sorting based on their relevance to the input design model. Each search method used by an SRT has limitations, the engineering users need to be cognizant of limitations of the search shape models. Currently, there are no standards or baseline criteria to evaluate and compare the effectiveness and accuracy of the retrieved models in a standard format without human subjective opinion.

In this context, the research presented in this paper seeks to address both these limitations by (a) developing a holistic set of comparison metrics for comparing the performance and effectiveness of SRT tools and (b) demonstrating a process for comparing the effectiveness of SRTs. This is accomplished by studying three commercially available SRTs.

Current measures for evaluating the performance and effectiveness of search engines and tools include *Recall*, *Precision*, and *Relative Recall* [6, 7]. They can be defined as

$$\text{Recall} = \frac{\text{relevant retrieved results}}{\text{relevant results in the database}}$$

$$\text{Precision} = \frac{\text{relevant retrieved results}}{\text{overall retrieved results}}$$

$$\text{Relative Recall}_i = \frac{\text{Retrieved results}_\text{i}}{\sum_\text{i}\text{Retrieved Results}}$$

However, these metrics have certain drawbacks, which are summarized below: Precision and Recall require knowledge on what is "*Relevant*"; defining what is relevant is not easy criteria for a pair of 3D shapes. The metric recall involves calculating the total number of relevant parts in a target database or web source; this is not simplistic as well as it depends on the criteria for relevance. The measure *Relative Recall* represents a cross-comparison between the retrieved results or outcomes.

There is a lack of knowledge of how end-users evaluate the retrieved information during search and retrieval tasks. In order to fill this gap, two model-matching methods for evaluating SRTs are proposed in this paper. The proposed methods identify the critical missing factors in the current evaluation system of SRTs that all results require human interpretation, which differs a lot based on the different perspectives of a user. Under the goal of providing an overall comparison among the existing SRTs, holistic criteria are provided in two sets of metrics to compare the SRTs:

Metric 1, provides the quantitative measures to evaluate the effectiveness of search results, and to quantify measurable characteristics such as execution time, and versatility of the input. Two new terms (*Relevance* and *Precision Sequence Metric — PSM*) are introduced in order to describe better the effectiveness and efficiency of the search process. The relevant results and correctly retrieved models in the sequence are decided by our two proposed similarity measurement tools, which will be described in the Methodology section.

1. <u>Effectiveness of the shape retrieval process underlying an SRT</u>: (Metric 1)

$$\text{Relevance} = \frac{\text{Relevant Retrieved Results}_\text{i}}{\sum_\text{i}\text{Retrieved Results}} \quad (i : \textit{Input Search Model Index})$$

$$\text{Precision Sequence Metric (PSM)} = \frac{\text{Correctly retrieved models in the Sequence}}{\text{Relevant Retrieved Results}}$$

2. <u>Computational Time</u>: Time is taken to retrieve and display similar parts from search engines

Table 1 Current 3D SRTs' approaches

	References	Shape model
Global feature	[16–21]	All models
Global feature distribution	[22–27]	All models
Spatial map	[28–36]	All models
Local feature	[37–41]	Mesh
Model graph	[42–49]	Solid except [49]
Skeleton	[50–52]	Volume
Reeb graph	[53–56]	Volume
View	[29, 57–60]	Mesh
Volumetric error	[61, 62]	Volume
Weighted point set	[63–65]	Mesh
Deformation	[66, 67]	Mesh

3. The versatility of input: Input model types and constraints

Metric set 2, provides qualitative evaluations of the SRT.

4. Search Preference option availability: the source of the search database (provided by users or not), ease of use in inputting and outputting the models
5. User-friendliness: decided by the user evaluation

Based on the current literature (as presented in the Literature review section), relevant models, and the final measures of the accuracy of the returned models are highly related, and the ranking of the relevant models is important. In this paper, two methodologies for defining the relevant models and their rank are developed with the goal of eliminating bias during evaluation. The relevancy between a pair of models is described as the Model Match Ratio (MMR) which is used for defining the relevance and precision metric for evaluating the SRTs. These are described in the Methodology section of the paper. Finally, results from the testing of the approach are presented using 3 commercial SRTs.

The remainder of this manuscript can be organized as follows. In Section 2, literature review based on current 3D model search methodologies and the evaluation criterions are discussed. Our proposed methodology that eliminate human translation on the geometries for providing quantitative measures are presented in Section 3. Evaluation results for three search engines based on our proposed algorithms are demonstrated in the later section. The discussion for illustrating the effectiveness and efficiency of the proposed evaluation measures are concluded in the last section.

2 Literature review

2.1 3D model search approaches:

A 3D model search engine collects a domain of relatively similar objects from a database through a defined input model. The earliest and common approach used in 3D model search engines is a keyword search, where all models in the databases have associated tags. Thus, a text query can be used to evaluate the models, and the rank can be extracted. These search engines are as follows: GrabCAD [8], Thingiverse [9], Shapeways [10], and Turbosquid [11]. Another query type is

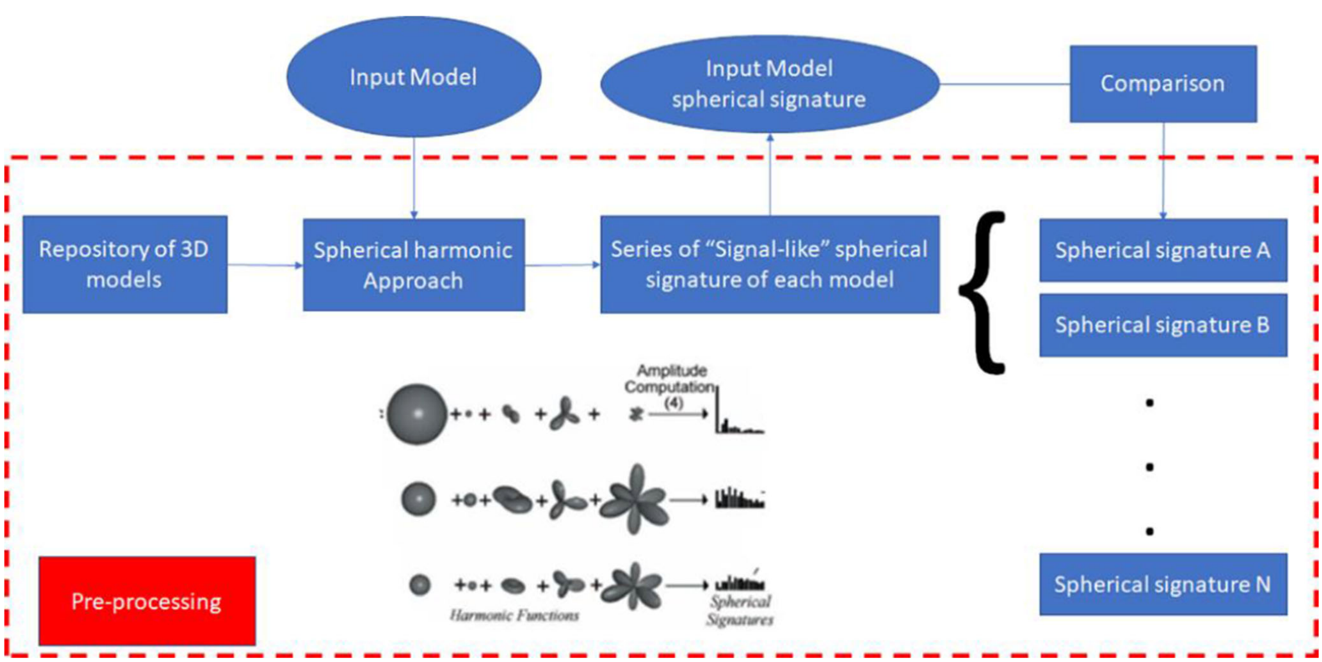


Fig. 2 Search engine approaches – 1 - Spatial map [28–36]

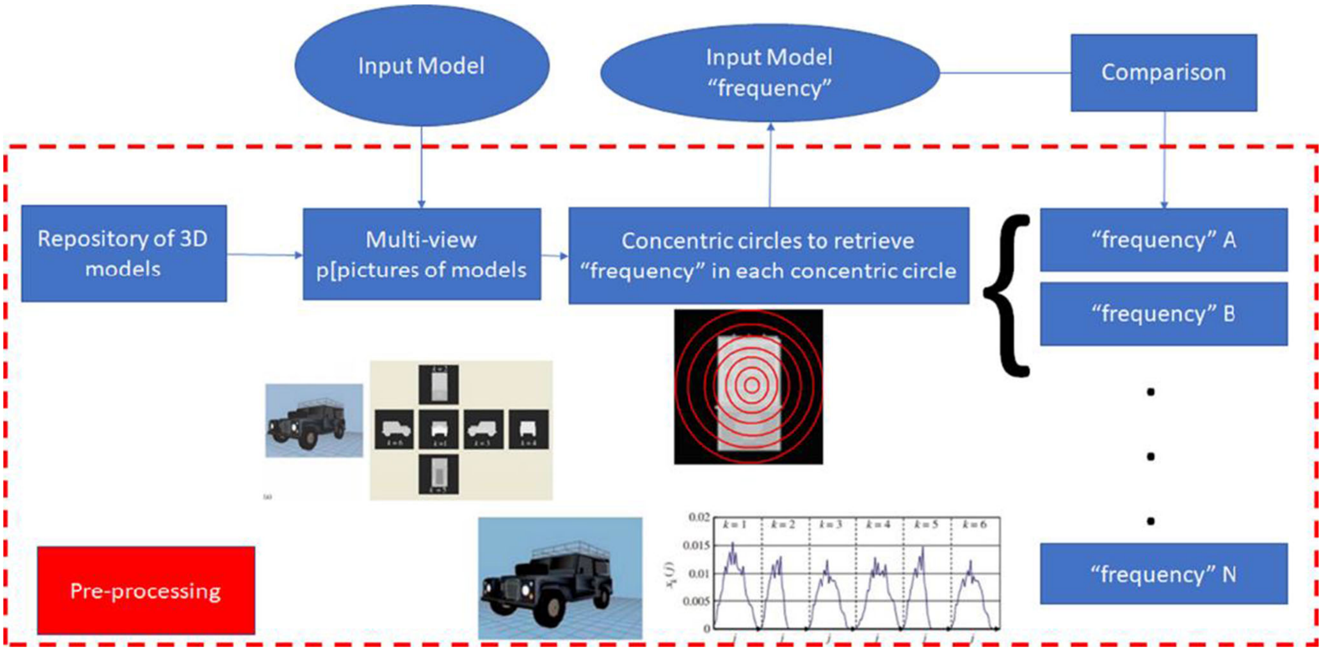


Fig. 3 Search engine approaches – 2 – Global feature distribution [22–27]

a sketch-based search. In the early stage, Rowe et al. [12] describes a system which can receive a 2D outline of a vessel as shape input and search through a series of 3D models of such vessels. Under the same condition, Chen et al. [13] reduce the models to a feature space that can be compared with others for producing a distance metric.

Besides the search tools which require a human-made database, there are many web-based querying engine examples. They are *3D Cafe* and *Avalon* that provide online repositories, and *CADlib*, *MeshNose,* and *Drexel University Browsing* only receive the text-based search of 3D model collections. Several other web-based search engines allow the search based on 3D shapes. For example, Corney et al. [14] developed a *ShapeSifter* that selects based on geometric constraints (surface area, convex hull volumes, etc.). Earlier, Suzuki [15] developed a search tool that allows the search matching grid-based or rotation invariant feature descriptors through 1500 VRML models. Osada [4] can also select three matching

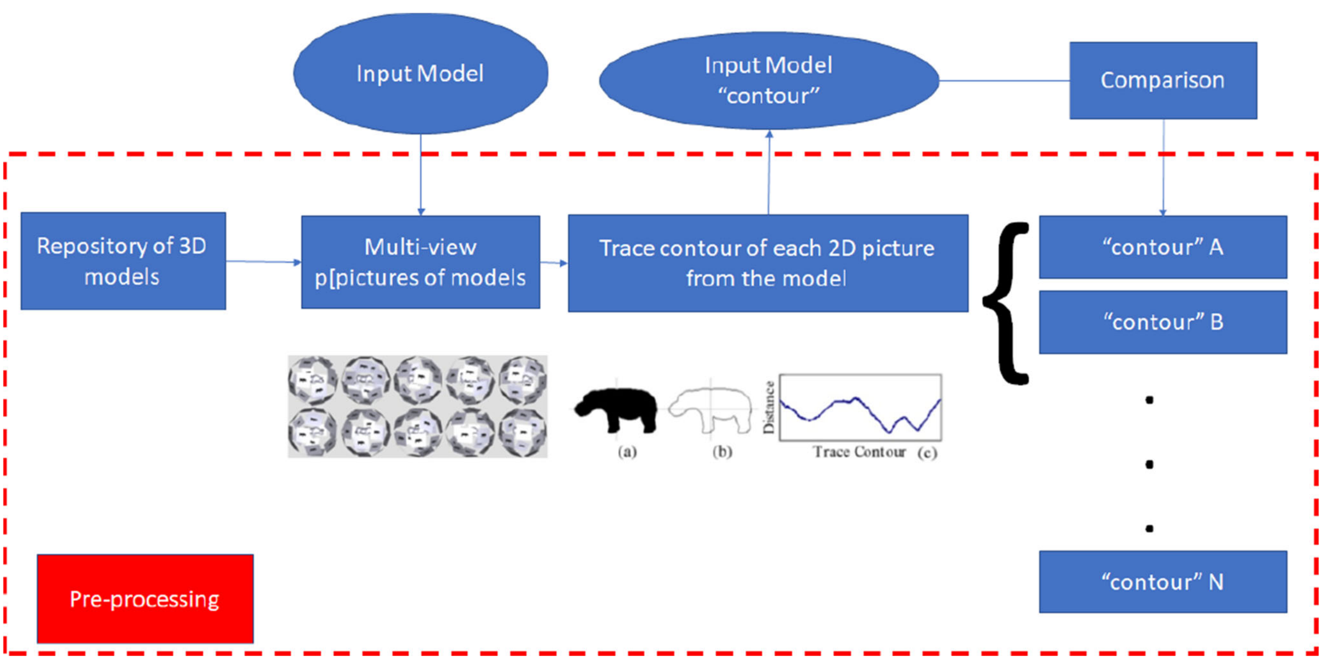


Fig. 4 Search engine approaches –3 – View [29, 57–60]

criteria (Gaussian curvature, Normal variations, Midpoints) through 133 models.

There are several other approaches to the development of search engines, which are shown in Table 1.

The major search approaches are explained in Figs. 2, 3, and 4.

From Figs. 2, 3, and 4, these search algorithms share a pattern — transform the complicated 3D models into 2D/1D shapes to simplify and speed up the search process. However, small features can be ignored during the transformation. Additionally, one feature's relative location concerning other features on one object is not considered in all the methods mentioned above. This search method could result in the return of non-matched objects with similar tree-branches.

2.2 Evaluation of search approaches underlying the SRTs:

Evaluation of the search approaches in the target SRTs is needed to determine if the identified search outcomes (from the SRTs) are relevant vis-a-vis the target input model created (and used to retrieve other design models of relevance using the SRTs). This can ensure that search queries lead to more accurate search and retrieval outcomes. With the increase in the number of 3D model search engines, attention should be shifted away from data retrieval algorithms to evaluating the performance of the SRTs.

The existing search engines evaluate the performance in terms of precision and recall [6, 7]. For example, Johnson and Crudge [68] mainly focus on evaluating the users' perspective and search tools experience. Similarly, Su et al. [69] studied the evaluation system in information retrieval. Other criteria used for evaluation are effectiveness, efficiency, human interaction, and overall satisfaction and success [70]. Haubl and Trifts [71] focused on the cost of search and improving the decision-making process in the search results. The other standard criteria used in evaluating the search engines are shown in Table 2.

Table 2 provides current evaluation methods for the search engines. These methods basically can be categorized into effectiveness and easiness. Current evaluation criterions for

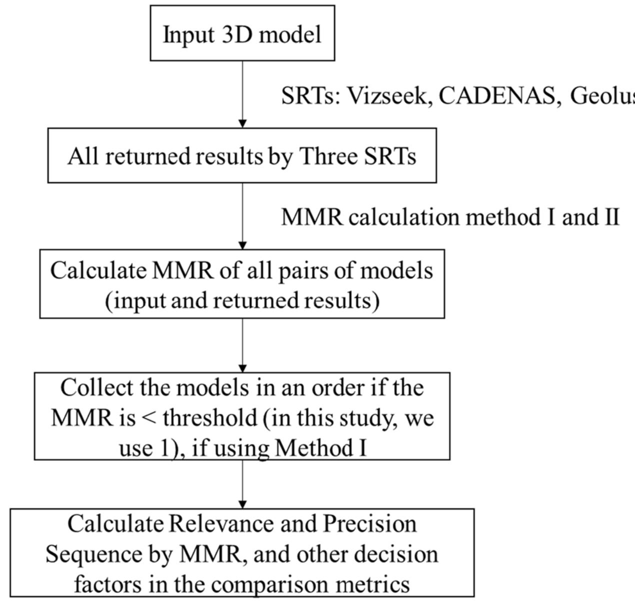


Fig. 5 Overall workflow of calculating the comparison metrics of three SRTs

deciding the effectiveness and easiness are based on human interpretation. The results from human assessment for analyzing the relevancy of the search returns can be hugely varied based on different interpretation aspects, thus cannot provides a standardized examination. The proposed methodology in the later section presents a quantitative evaluation approach without human interpretation on the geometries for the SRTs.

3 Methodology

As discussed earlier, the key issues that need to be addressed are as follows: develop an approach to eliminate the human judgment in establishing the relevant models, since the relevant models are used in establishing the performance metrics of set 1/(Relevance and Precision Sequence Matrix).

The development of a quantitative method measuring the similarity between a pair of models (the input model and the retrieved model) termed the "Model Match Ratio" (MMR) is proposed. Two methods are proposed for computing the

Table 2 Evaluation of the search engine criterions

Evaluation criterion	Capability	Reference
Usability of search tools	Availability of the search file type. Overall ease of use	71
Effectiveness	precision and relevance of returned results	57, 58
Output file displayed	Results readability/exportable or not	72
Computational time and cost of the search	Better decision-making	70
Convenience	Database construction by the user or not. Accessibility	72

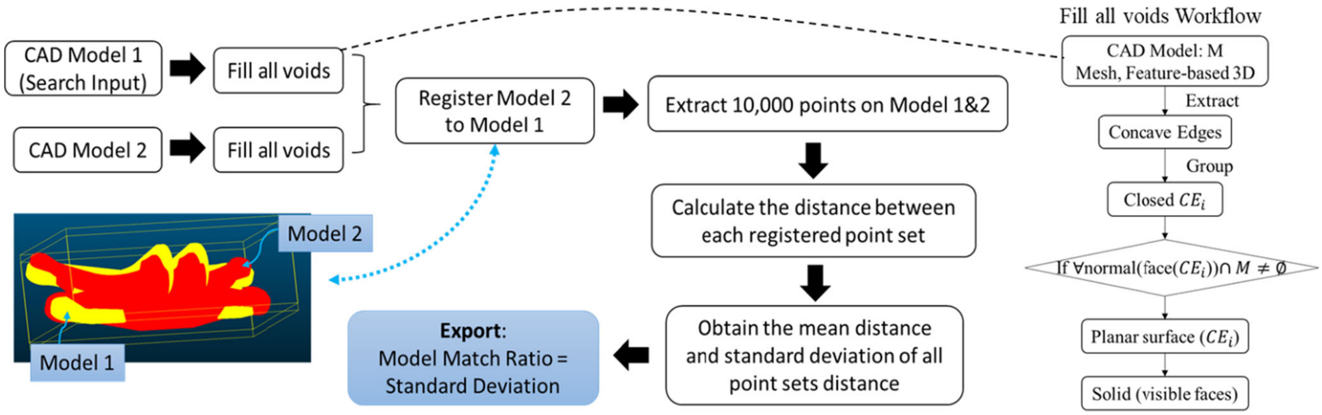


Fig. 6 Model Match Ratio (MMR) Calculation Method 1

MMR. The 1st computation method provides the maximum overlapping zone between each pair of the models; the 2nd method retrieves the skeleton-based models representing the feature combination within one geometry. The rank based on the similarity index can decide how many models are correctly retrieved from the input.

The overall approach to compute comparison metrics for SRTs is shown in Fig. 5.

Figure 5 represents the overall evaluation process for a pair of models using the MMR value, which is defined to represent the model relevancy. The related retrieved model for computing relevance and Precision Sequence Metric (PSM) is defined when its corresponding MMR <1. The models which have an MMR ≥1 will be considered the non-related retrieved models.

Assessing the similarity between shapes can be posed as the problem of defining an optimization function: $\max(X[\alpha] \cap Y[\beta])$, taking a pair of objects, and allowing both of them to rotate to find the maximum overlapping volume. Often a higher number represents a larger similarity. Currently, the transformation of the input geometries is to optimize the overlapping zone in between. Here, two methods are provided to define the relevance of retrieved models, to compute performance measures of the SRTs. Model Match Ratio is defined for a pair of models and represents the maximum overlapping zone between the 2 models. It is used for determining the Relevance and Precision Sequence Metric in our comparison metrics.

Two measures of SRTs are listed:

$$\text{Relevance}_i = \frac{\text{Related retrieved Results}_\text{i}}{\sum_\text{i}\text{Retrieved Results}}$$

Precision Sequence Metric

$$= \frac{\text{Correctly retrieved models in the Sequence}}{\text{Related retrieved Results}}$$

Where: *Relevant Retrieved Results*$_i$ = Model Match Ratio (MMR)

$\sum_\text{i}$Retrieved Results=Total number of models returned by the SRTs

Correctly retrieved models in the Sequence=Number of models in the correct order based on the descending order of MMR

The two methods developed for calculating MMR are shown in Figs. 6 and 7. Method 1 analyzes the entire 3D model topological information, including small features. The distance between pairs of random points on the two models after their registration is then calculated. The resulting standard deviation of all points is defined as MMR, where the more significant deviation represents the two models that are more dissimilar. In contrast, the smaller MMR represents higher similarity. Method 2 follows a different approach using the medial axis of the 3D model and has a smaller computational complexity. However, it could induce failure between

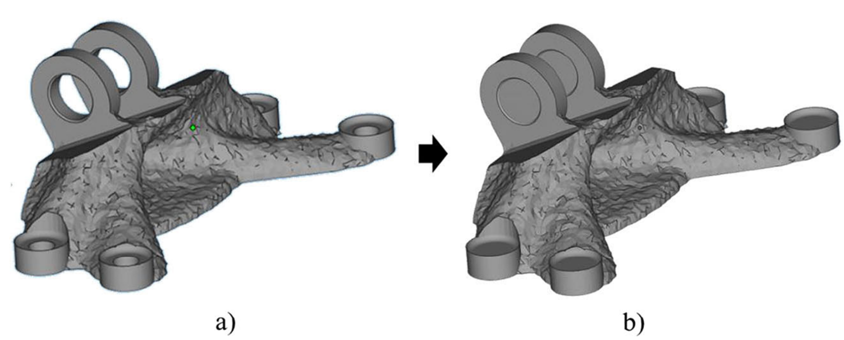


Fig. 7 Fill all voids operation. **a** Before filled voids operation, **b** After filled voids operation

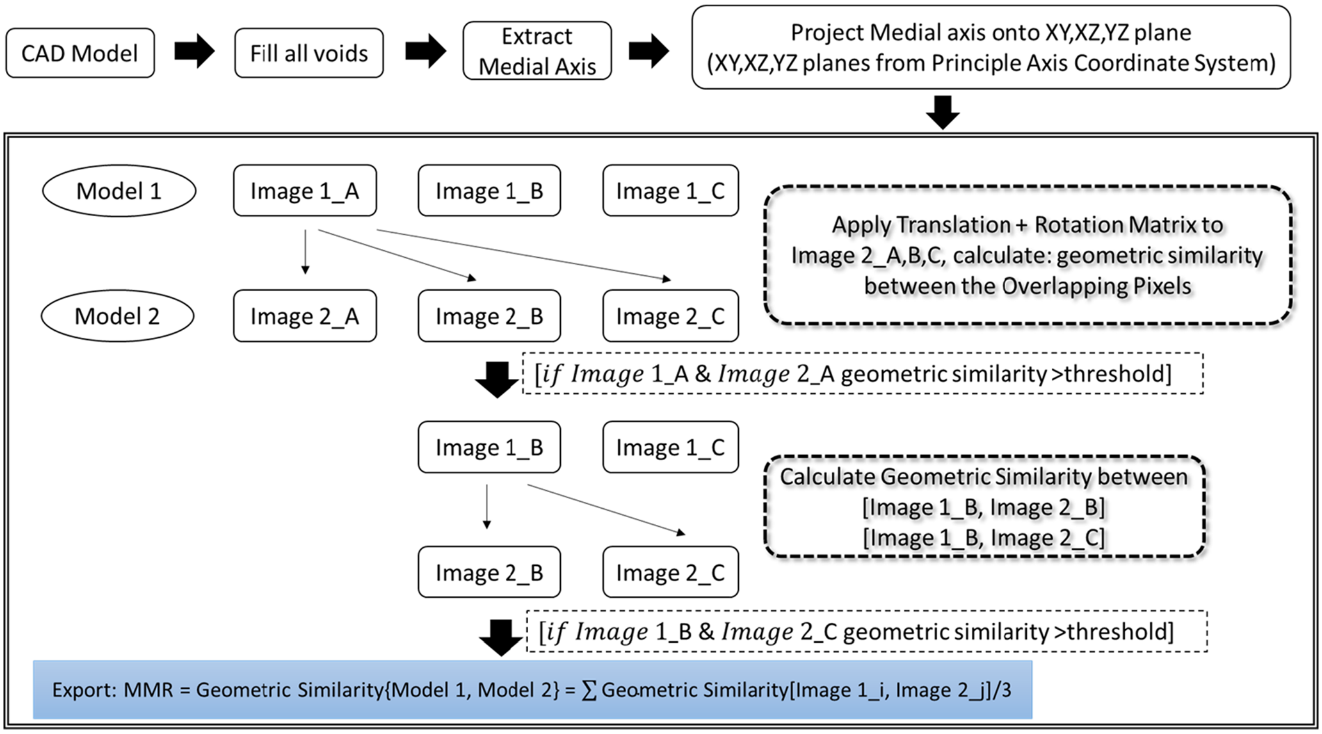


Fig. 8 Model Match Ratio (MMR) Calculation Method 2

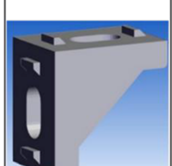
any models made by revolving features, such as cylinders and cone shapes.

Figure 6 shows that the 3D model topological information, including overall geometric shape and small feature details, is captured during the comparison. The first step in Method 1 is to fill all voids in both geometries to avoid any erroneous registration caused by the voids in the volumes. To fill all voids in the geometry, all concave edges need to be extracted. Then, these concave edges are selectively grouped by checking whether the normal of their adjacent facet on the geometry intersects the geometry. If the concave edge satisfies the abovementioned condition, these edges can be formed into the edge-loop. Each individual edge-loop will be filled with planar surface for constructing the filled solid geometry. This step is described in Fig. 6 right. Figure 7 presents an example with the voids existing in the geometry, after process through the "fill all voids" operation, the planar surfaces are created to construct the full solid body.

The second step to match a pair of models is to register models. The iterative closest point (ICP) algorithm [72] is adopted to transform and align one model to the other. The search model (Model 1) will be used as the reference model, and Model 2 will be the one that needs to be transformed. Besides, there is no pre-processing of the 3D models, such as the secondary transformation from 3D to 2D or other formats. However, it is computationally time-consuming. Hence, it is not suitable as a full search engine but still useful for evaluating the smaller retrieved set. Furthermore, it cannot work with sketched search engines since 2D drawings cannot be accepted as input.

Figure 8 presents the second method for computing MMR that is used to define relevance between a pair of models. Compared with Method 1 in Fig. 6, Method 2 extracts the medial axis in the geometry which represents the overall skeleton within the model. Instead of matching two solid models, Method 2 simplify the solid geometry into the tree-shape

Fig. 9 Input search models to the search engines

	Model a	Model b	Model c	Model d
Input Model				

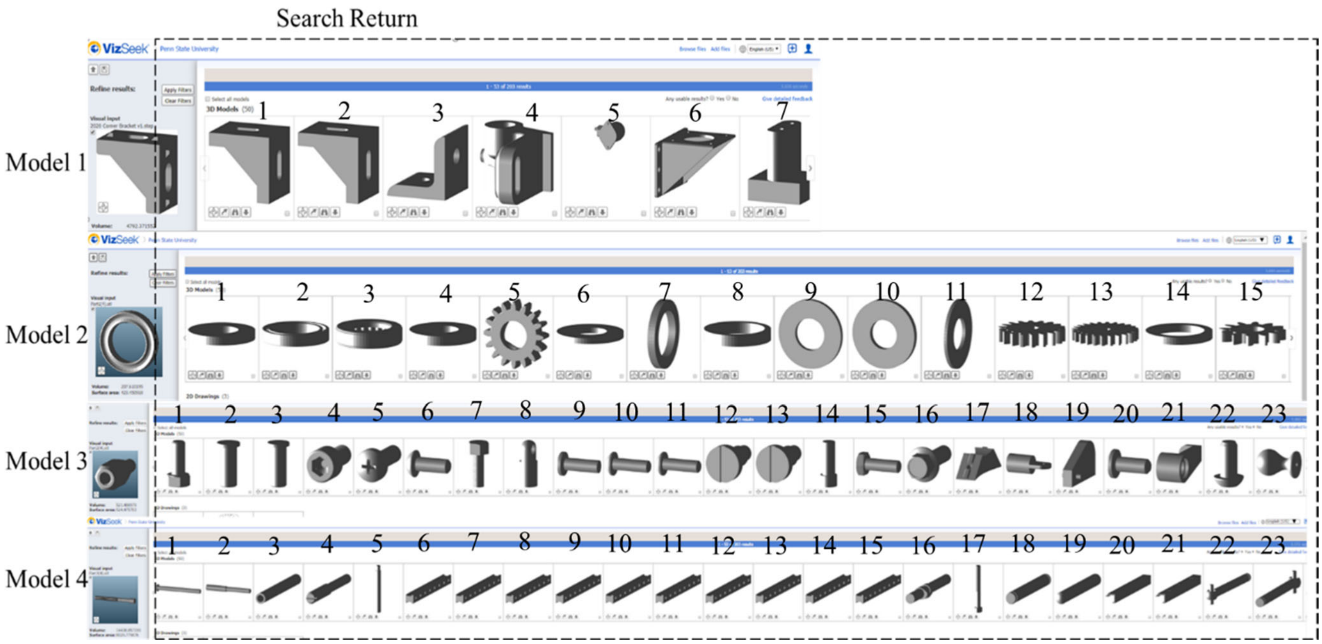


Fig. 10 Search output by Vizseek for Models 1–4

structure which has a less computational time compared with Method 1. Due to its transformation from 3D to multi-view 2D images of its skeleton shapes, it can also be used to evaluate the sketch-based search tools as well. However, due to the medial axis constraints, there are no differences in the medial axis of revolved/symmetrical components. The medial axes of these features are straight lines, hence limiting the usefulness of this method.

4 Results and discussion

The approach proposed (and discussed in the previous section) has been implemented in Matlab and Python, using an Intel® Core™ i5-6600 CPU @3.30GHz 3.31GHz computer.

Four example parts/design models (Fig. 9) were processed through the implemented software to illustrate the comparison metrics results of three SRTs. These four example parts were obtained from existing literature; the search outcomes from the 3 SRTs are discussed in this section.

4.1 Data and results using MMR (Method 1)

In the first retrieval, Vizseek was evaluated using MMR (the Method 1). In Fig. 10, the search outputs are listed after using Vizseek.

Figure 10 shows all search outputs from Vizseek for the four input parts. The results show that several identical parts were retrieved since the database had multiple instances of the same part are collected, including the identical models. In the search results of Model 1, several models are identical. For example, output 1 and 2 and output 5 and 7 of input Model 1 are considered the same output when the computed MMR are the same of these searched results. Five unique outputs are

Table 3 MMR result of models 1–4 search results

Model 1	Output 1 0.647	Output 2 0.647	Output 3 0.913	Output 4 1.730	Output 5 N/A
	Output 6 0.882	Output 7 N/A			
Model 2	Output 1 0.404	Output 2 0.231	Output 3 0.212	Output 4 0.501	Output 5 0.511
	Output 6 0.290	Output 7 0.087	Output 8 0.220	Output 9 0.442	Output 10 0.442
	Output 11 0.424	Output 12 0.994	Output 13 0.994	Output 14 0.116	Output 15 0.892
	Output 16 0.983	Output 17 0.882	Output 18 1.031	Output 19 0.507	Output 20 0.907
	Output 22 1.107	Output 23 0.758	Output 24 0.670	Output 25 1.051	Output 26 1.016
	Output 27 0.980	Output 28 1.168	Output 29 0.236	Output 30 0.235757	
Model 3	Output 1 0.606	Output 2 0.326	Output 4 0.437	Output 5 0.346	Output 6 0.411
	Output 7 0.337	Output 8 0.404	Output 9 0.302	Output 12 0.855	Output 13 0.508
	Output 14 0.746	Output 15 0.342	Output 16 200.000	Output 17 0.425	Output 18 0.846
	Output 19 0.726	Output 20 100.000	Output 22 0.941	Output 23 1.144	Output 24 0.329
Model 4	Output 1 0.136	Output 2 0.886	Output 3 0.728	Output 4 0.880	Output 5 0.566
	Output 16 1.394	Output 17 0.788	Output 18 0.813	Output 19 0.578	Output 20 3.587
	Output 22 0.960	Output 27 0.519	Output 28 0.505	Output 30 0.931	Output 31 0.748
	Output 49 0.840				

Table 4 Effectiveness of Vizseek of Models 1–4 by Method 1

Model #	Relevance: Related retrieved models/∑All retrieved models	Precision sequence: Correctly retrieved models in a sequence/ related retrieved models
Model 1	4/50	3/4
Model 2	29/50	8/29
Model 3	20/50	8/20
Model 4	16/50	5/16

identified based on the MMR. The parts are shown in the sequence as retrieved.

The MMR for each output model is represented in Table 3.

The relevance and Precision Sequence Metric based on each output's MMR for Models 1–4 is shown in Table 4.

Table 4 presents the analytic results of Vizseek by considering the relevance and precision sequence. When Model 1 is used as the input geometry, the search returns 50 models as a default setting. Model 8 and beyond have large MMR computed by Method 1. Thus, they are not counted to be related retrieved models. The remaining search returns of Model 1 (Output #8–50) are not presented in this paper due to their high MMR. The precision sequence for Model 1 requires counting the correctly retrieved models, output 1,2, and 3 and output 1, 2, and 6 are in the correct order based on their ascending MMR value. Thus, the correctly sequenced outputs for Model 1 are three models.

In the second retrieval process, four inputs are sent to the CADENAS. Figure 11 presents the searched returns of these four models.

The evaluation (MMR) of each output of every model by using Method 1 is shown in Table 5.

The relevance and Precision Sequence Metric based on each output's MMR of Models 1–4 is shown in Table 6.

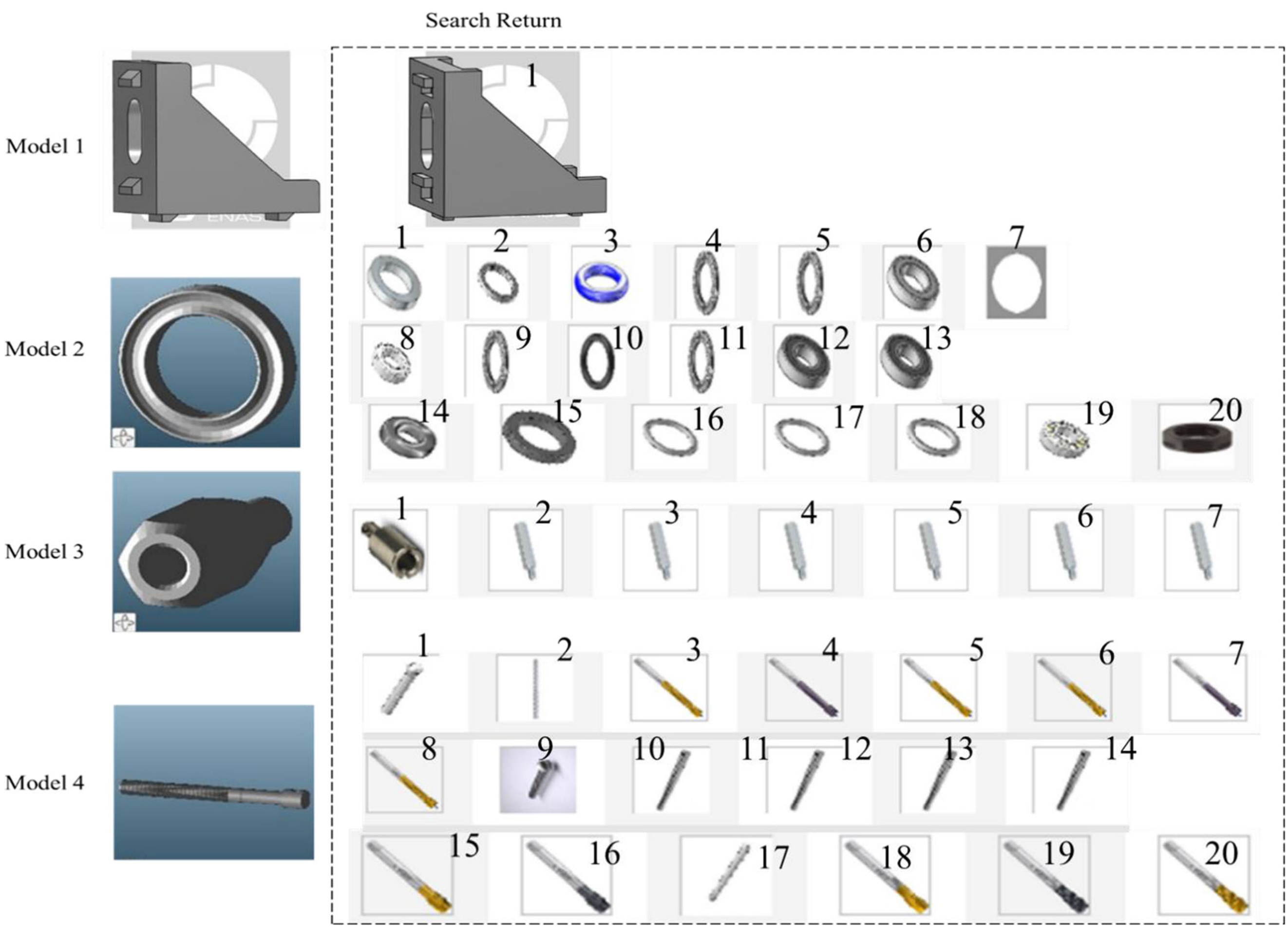


Fig. 11 Search output by CADENAS of Models 1–4

Table 5 MMR result of models 1–4 search results

Model 1	Output 1				
	0.302				
Model 2	Output 1	Output 2	Output 3	Output 4	Output 5
	0.102	0.143	0.126	0.096	0.096
	Output 6	Output 7	Output 8	Output 9	Output 10
	0.282	0.228	0.173	0.285	0.091
	Output 11	Output 12	Output 13	Output 14	Output 15
	0.091	0.415	0.103	0.416	0.328
	Output 16	Output 17	Output 18	Output 19	Output 20
	0.128	0.134	0.135	0.440	0.107
Model 3	Output 1	Output 2	Output 3	Output 4	Output 5
	0.219	0.233	0.233	0.233	0.233
	Output 6	Output 7			
	0.234	0.233			
Model 4	Output 1	Output 2	Output 3	Output 4	Output 5
	0.508	0.355	0.403	0.402	0.404
	Output 6	Output 7	Output 8	Output 9	Output 10
	0.771	0.773	0.775	0.033	0.091
	Output 11	Output 12	Output 13	Output 14	Output 15
	0.091	2.256	2.250	0.193	0.193
	Output 16	Output 17	Output 18	Output 19	
	0.855	0.680202	0.335601	0.335703	

In the third search, same inputs are sent to the Geolus. The search returns are shown in Fig. 12.

The evaluation (MMR) of each output from the Geolus of every model by using Method 1 is shown in Table 7 and 8.

Metric 1 is presented in Fig. 13, which includes three criteria: Versatility of input, effectiveness of the shape retrieval process underlying an SRT: relevance and Precision Sequence Metric, and computational time.

The relevance and Precision Sequence Metric for the three SRTs are combined into one figure to select the best performance search engine, as shown in Figs. 14 and 15. Based on these two figures, CADENAS always provides the best relevance evaluation, followed by Geolus and then Vizseek. It means that CADENAS can always provide more relevant models compared to the other two SRTs.

However, if only focusing on the correctly ranked retrieved models, Geolus provides a better sequence of the retrieved results (from **Fig. 15**).

4.2 Data and results by Method 2

The evaluation metric by using MMR method 2 is provided in Fig. 16 of three SRTs. The second method mainly focuses on the medial axis of the geometry, while the first focuses on the overall geometry comparison. If a cylinder and a rectangular block are compared using Method 2, the corresponding results indicate that these two geometries are similar; however, Method 1 results conclude that these two models are different. Method 2 emphasizes the sweeping direction in the CAD modeling system, while Method 1 targets to discover the overall volumetric overlap among the inputs.

The relevance and Precision Sequence Metric calculated using MMR (Method 2) are selected to represent the best performance search engine in Figs. 17 and 18. Based on Fig. 17, the relevance evaluation by Method 2 returns the same result with Method 1. The CADENAS returns the most numbers of the relevant models, while the Vizseek returns the least.

From Fig. 18, the ranking based on PSM evaluation is Geolus, CADENAS, and Vizseek. Based on the part examples and criteria discussed, Geolus provides a better-sequenced output based on part design similarity attributes compared to CADENAS and Vizseek. This conclusion is in agreement with the result of Method 1 discussed earlier.

Both MMR calculation approaches indicate that Geolus has the most numbers of correctly sequenced outcomes based on the model similarity, followed by CADENAS and Vizseek.

Comparing the examples shown in Figs. 14, 15, 17, and 18, the capabilities and advantages of two MMR calculation methods can be summarized as follows:

1. Two MMR calculation methods lead to varied "***Relevance***" and "***Precision Sequence Metric***" based on the same search under the same size database
2. MMR (Method 2) is faster than MMR (Method 1) since it extracts the medial axis and projects on to 2D planes. The comparisons are based on the 2D comparison, while the

Table 6 Effectiveness of CADENAS of Models 1–4 by Method 1

Model #	Relevance: Related retrieved models/∑All retrieved models	Precision sequence: Correctly retrieved models in a sequence/related retrieved models
Model 1	1/1	1/1
Model 2	20/20	7/20
Model 3	7/7	4/7
Model 4	19/19	7/19

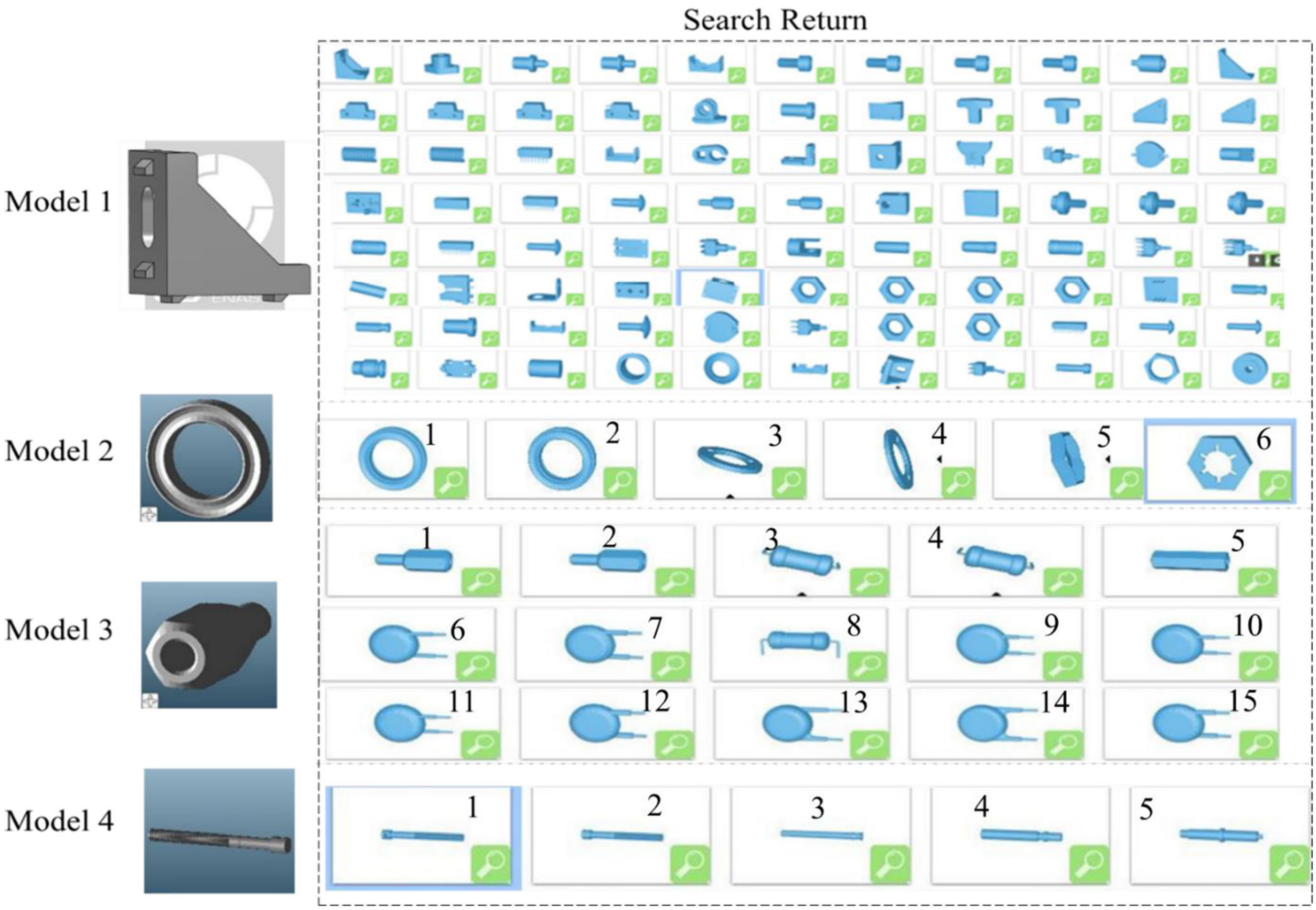


Fig. 12 Search output by Geolus of Models 1–4

MMR (Method 1) compares the registered 3D model variance, which is more time-consuming.

Table 7 MMR result of models 1–4 search results

Model 1	Output 1	Output 2	Output 16	Output 18	Output 28
	0.685	NaN	NaN	3.208	0.792
	Output 29	Output 40	Output 57	Output 59	Output 60
	1.264	NaN	8.513	NaN	2.378
	Output 79	Output 84	Output 99	Output 106	Output 143
	1.260	0.685	8.518	2.652	NaN
Model 2	Output 1	Output 2	Output 3	Output 4	Output 5
	0.005	0.005	0.216	0.211	0.378
	Output 6				
	0.378				
Model 3	Output 1	Output 2	Output 3	Output 4	Output 5
	0.006	0.006	0.534	0.534	0.349
	Output 8	Output 46	Output 47		
	0.534	0.345	0.345		
Model 4	Output 1	Output 2	Output 3	Output 4	Output 5
	0.023	0.023	0.648	1.192	0.900

3. Based on relevance evaluation (MMR Methods 1 and 2), the rank of three SRTs are as follows: CADENAS, Geolus, and Vizseek
4. Based on PSM evaluation (MMR Methods 1 and 2), the rank of three SRTs are as follows: Geolus, CADENAS, and Vizseek
5. MMR (Method 1) captures the real 3D model (including overall geometric shape and small feature details) during comparison
6. MMR (Method 1, 2) provides a similarity percentage based on Model Match Ratio

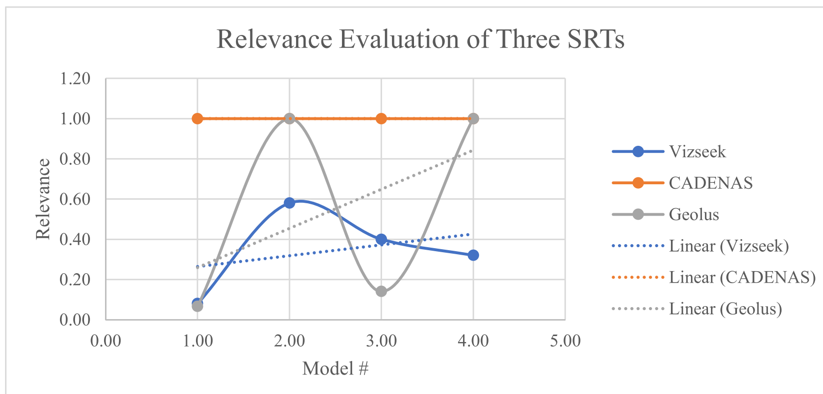
Table 8 Effectiveness of Geolus of Models 1–4 by Method 1

Model #	Relevance: Related retrieved models/∑All retrieved models	Precision sequence: Correctly retrieved models in a sequence/related retrieved models
Model 1	10/152	5/10
Model 2	6/6	5/6
Model 3	8/57	5/8
Model 4	5/5	4/5

Computation Time	Vizseek 1	Vizseek 2	Vizseek 3	Vizseek 4	CADENA	CADENA	CADENA	CADENA	Geolus 1	Geolus 2	Geolus 3	Geolus 4
Input model types	24 types (3D models, 2D sketches)	24 types (3D models, 2D sketches)	24 types (3D models, 2D sketches)	24 types (3D models, 2D sketches)	.STL	.STL	.STL	.STL	.STL	.STL	.STL	.STL
Relevance	**4/50**	**29/50**	**20/50**	**16/50**	**1/1**	**20/20**	**7/7**	**19/19**	**10/152**	**6/6**	**8/57**	**5/5**
Precision Sequence	**3/4**	**8/29**	**8/20**	**5/16**	**1/1**	**7/20**	**4/7**	**7/19**	**5/10**	**5/6**	**5/8**	**4/5**
Search Engine database size	**3000**	**3000**	**3000**	**3000**	**unknown**	**unknown**	**unknown**	**unknown**	**8650**	**8650**	**8650**	**8650**
Retrieval Time	**15.16s**	**15.11s**	**12.02s**	**21.04s**	**1.44s**	**1.57s**	**3.86s**	**3.06s**	**4.3s**	**1s**	**1s**	**1s**

Fig. 13 Evaluation Metric 1 by MMR Method 1

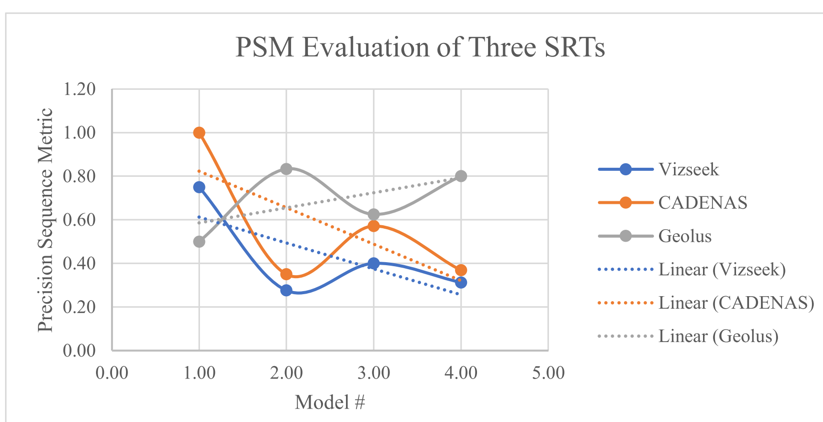
Fig. 14 Relevance evaluation of three SRTs by MMR Method 1



7. MMR (Method 1) computationally time-consuming, hence not suitable as a full search engine
8. MMR (Method 1) only works with 3D models (e.g., 2D drawings cannot be used as input)
9. MMR (Method 2) may not distinguish the revolved feature shape (cylinder or rectangle bar)

As mentioned in the Introduction section, the other two criteria can be used for evaluation — availability of Search Preference options and user-friendliness, which need to be evaluated by the users. As a reference, Vizseek and Geolus Database were input by our web crawler results, which leads to the same database size in both. CADENAS has a database

Fig. 15 Precision Sequence Metric (PSM) evaluation of three SRTs by MMR Method 1



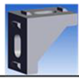
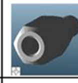
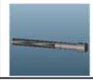
Computation Time	Vizseek 1 	Vizseek 2 	Vizseek 3 	Vizseek 4 	CADENAS 1 	CADENAS 2 	CADENAS 3 	CADENAS 4 	Geolus 1 	Geolus 2 	Geolus 3 	Geolus 4 
Input model types	24 types (3D models, 2D sketches)	24 types (3D models, 2D sketches)	24 types (3D models, 2D sketches)	24 types (3D models, 2D sketches)	.STL	.STL	.STL	.STL	.STL	.STL	.STL	.STL
Relevance	**4/50**	**18/50**	**19/50**	**20/50**	**1/50**	**14/20**	**7/7**	**10/19**	**11/152**	**4/6**	**3/57**	**5/5**
Precision Sequence	**2/4**	**10/18**	**8/19**	**5/20**	**1/1**	**10/14**	**7/7**	**6/10**	**5/11**	**4/4**	**3/3**	**5/5**
Search Engine database size	8650	8650	8650	8650	N/A	N/A	N/A	N/A	8650	8650	8650	8650
Retrieval Time	15.16s	15.11s	12.02s	21.04s	1.44s	1.57s	3.86s	3.06s	4.3s	1s	1s	1s

Fig. 16 Evaluation Metric 1 by MMR Method 2

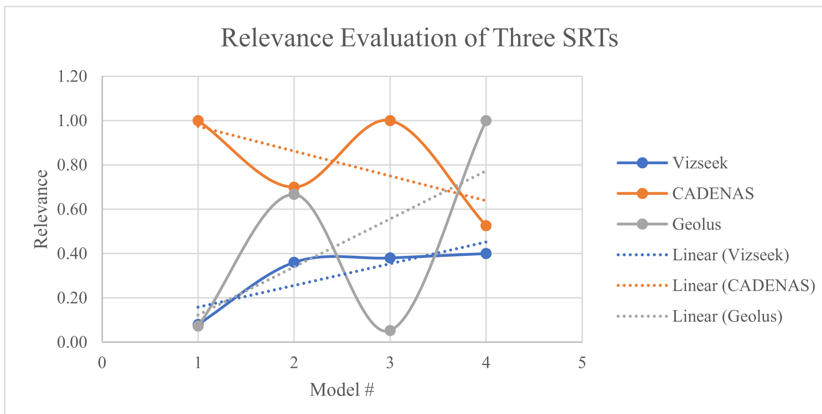


Fig. 17 Relevance evaluation of three SRTs by MMR method 2

that mostly includes 3D CAD supplier catalogs and is not accessible to the user. The user evaluation determines the comparison metrics 2 for the SRT comparison (Table 9), which includes Search Preference option availability (ease of use of inputting and outputting, etc.) and user-friendliness. In this metric, one represents the poor user experience, and five means the best.

As can be seen from Fig. 18, Vizseek has an overall best user experience except for the output types since the output file types are limited. In contrast, Geolus has the average poor user experience due to its way of constructing the search database. It has limited data input formats, and it takes a long time to process the database. CADENAS is an online-based search tool that has a limitation of the database, since it mostly

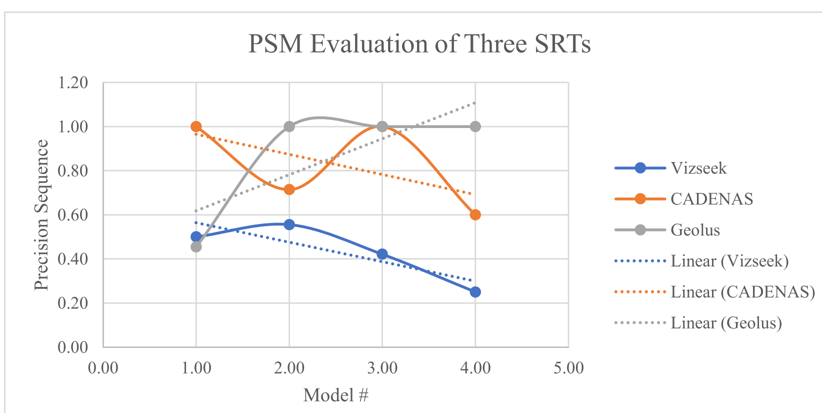


Fig. 18 Precision Sequence Metric (PSM) evaluation of three SRTs by MMR Method 2

Table 9 Evaluation Metric 2 of three SRTs

Source to search	GEOLUS Database	VIZSEEK Database	CADENAS Internet
Input Types	1	5	1
Output Types	5	1	3
User-friendliness	1	5	3

includes 3D CAD supplier catalogs. It does not have the capability to allow users to add parts to the database.

5 Conclusion

Due to the high demand for design optimization, 3D model search based on geometric similarity becomes more popular than search through semantic input. The existing commercial software for searching 3D models has different aspects in configuring the similarity between a pair of 3D models. However, the distinct search results show a strong need to develop comparison metrics to study the performance of Shape Retrieval Tools (SRTs). This paper presented holistic comparison criteria to perform such comparisons as well as proposed two methods to accomplish this objective. The two methods were demonstrated using several 3D designs on three SRTs (Vizseek, CADENAS, and Geolus). The proposed approach removes the need for subjective human comparisons in determining the degree of similarity between two pairs of 3D models as part of the shape retrieval process. The effectiveness and performance of the 3 SRTs were compared based on several criteria, including the user-friendliness of these tools. The approach outlined in this paper for comparing the performance of SRTs can also be adapted to creating an automated process to evaluate the search/retrieval process involved, which can be a significant saving in time and effort for design-manufacturing activities. The proposed SRT evaluation methods can be further optimized and integrated with machine learning to develop a fast, stable retrieving 3D model engine for academic researchers. In addition, the industrial application users can utilize the proposed approach to evaluate the accuracy the search engine returns without any human perceptions. Future research activities can extend the research approach discussed, including developing a faster search heuristic for such design model retrievals as well as extending the comparison to other SRTs (including sketch-based SRTs).

Author contribution Dr. Xiao developed the computational algorithms, 3D model database, and was the major contributor in writing the manuscript, and revised the paper. Dr. Joshi revised the algorithms, and revised the paper. Dr. Cecil revised the algorithms, and revised the paper. All authors read and approved the final manuscript.

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Declarations

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Consent to publish Not applicable.

Competing interests The authors declare no competing interest.

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